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Deposit Insurance Adoption and Bank Risk-Taking: the Role of Leverage*

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Abstract

Explicit deposit insurance is a crucial ingredient of modern financial safety nets. This paper investigates the effect of deposit insurance adoption on individual bank leverage. Using a panel of banks across 117 countries during the period 1986-2011, I show that deposit insurance adoption pushes banks to increase significantly their leverage by reducing their capital buffer. This increase in bank leverage then translates into higher probability of insolvency. Most importantly, I bring evidence that deposit insurance adoption has important competitive effects: I show that large, systemic and highly leveraged banks are unresponsive to deposit insurance adoption.

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1 Introduction

Understanding the determinants of excessive bank risk-taking is a crucial issue since the outbreak of the financial crisis. This research agenda has received a lot of attention and many suspects have been identified. Among them, excessive leverage is now rightly considered as one of the primary causes of the Great Recession (Adrian and Shin (2010), Brunnermeier (2009) and Acharya et al. (2012)). Highly leveraged financial institutions increase significantly the risk of contagion as well as they have the potential to disrupt durably the functioning of some financial markets when facing unexpected shocks. The credit supply may also shrink sharply in case of rapid and simultaneous deleveraging process. On the other hand, recent work have reaffirmed the prominent role of regulation in providing correct incentives to banks. An intense debate concerning the adverse impact of state guarantees has been revived by the massive bailouts and almost full guarantees provided to the financial industry after the bankruptcy of Lehman Brothers. Interestingly, similar concerns arose when a large number of countries started to implement an explicit deposit insurance scheme. These insurance schemes suffer from the same moral hazard issue as state guarantees by giving banks strong incentives to adopt risky behaviors thereafter. The general purpose of this paper is to explore the relation between deposit insurance adoption and bank leverage, paying particular attention to the possible heterogeneous responses of banks.

The main benefit from introducing a deposit insurance scheme is to protect small and presumably uninformed depositors against bank failures. Accordingly, deposit insurance should rule out bank runs and inefficient liquidation of profitable projects (Diamond and Dybvig (1983)). However, deposit insurance adoption is likely to mitigate, if not eliminate, market discipline by depositors as shown by Martínez-Peria and Schmukler (2002), Demirguc-Kunt and Huizinga (2004) or Karas et al. (2013). In absence of actuarially fair premia, deposit insurance poses a crucial moral hazard issue: it provides to banks strong incentives to increase their risk-taking to exploit the put option value of deposit insurance (Merton (1977), Marcus and Shaked (1984), Keeley (1990) and Pennacchi (2006)). In particular, deposit insurance schemes with flat premia should result in reducing significantly bank capital buffer (Bond and Crocker (1993)). Finally, if the deposit insurance fund is unable to efficiently manage this build-up of excessive risk, the ultimate effect of deposit insurance might be to make depositors more exposed to bank failure.

This paper investigates the effects of deposit insurance adoption on bank risk-taking, and especially on bank leverage. More importantly, it explores extensively the likely heterogeneity among banks' responses. For this purpose, I use a panel data set covering banks in 117 countries over the period 1986-2011 together with a newly updated database on deposit insurance schemes around the world. Deposit insurance adoption is found to increase bank risk-taking by significantly reducing bank capital buffer: the *Capital-to-Assets ratio* of banks decreases by around 15% after the implementation of deposit insurance scheme. This reduction of bank capital buffer translates into higher insolvency risk: the distance-to-default of banks decreases by 15% after deposit insurance adoption. However, these effects are not uniformly distributed across banks : large, systemic and initially highly leveraged banks are unresponsive to deposit insurance adoption.

Previous research has investigated the adverse impact of deposit insurance adoption on bank risk-taking (Kane (1989), Wheelock (1992), Wheelock and Wilson (1995), Demirguc-Kunt and Detragiache (2002), and Laeven (2002)). All these studies conclude that explicit deposit insurance can be related to an increase in the probability of bank distress or a decrease in banking stability. Recently, DeLong and Saunders (2011) confirm this increase in bank risk-taking following deposit insurance adoption by studying the one that occurred in the USA in 1933. Using internal loan ratings in Bolivia, Ioannidou and Penas (2010) show that banks are more likely to originate riskier loans after deposit insurance implementation. However, all these papers usually focus on a specific country (mainly the USA) or a limited set of countries.[1] When covering a large number of countries, they generally work at an aggregate level.[2] In this regard, the present paper does not consider aggregate indicators of financial stability but bank-level measurements of risk-taking: it is among the first to work at the bank-level with a large cross-country data set. It is important because aggregate data may mask valuable micro level patterns as the rest of the analysis will show. In addition, most of the previous work focus on the impact of deposit insurance on asset risk or volatility risk. In contrast the present paper investigates the consequences of deposit insurance on bank capital buffer. This paper hence contributes

[1] DeLong and Saunders (2011), Ioannidou and Penas (2010) or Martínez-Peria and Schmukler (2002)

[2] Demirguc-Kunt and Detragiache (2002),Demirguc-Kunt and Huizinga (2004) or Beck (2008) for instance

to the literature by quantifying the impact of deposit insurance adoption on individual bank risk of insolvency and by underlying the prominent role of leverage in this process.

The adverse effects of deposit insurance are not expected to be uniform across banks. As underlined by Calomiris and White (1994), Demirguc-Kunt and Kane (2002) and Demirgüç-Kunt et al. (2008), deposit insurance adoption should mainly benefit to small banks. Similarly, systemic banks that benefit from implicit state guarantees (the *too-big-to-fail* hypothesis) should not react to deposit insurance adoption because they escape market discipline even before adoption. Finally, in absence of actuarially fair premia, well-capitalized banks implicitly subsidize highly leveraged banks (Marcus and Shaked (1984)). In addition, these well-capitalized banks have much more room for substituting deposits to equity. We thus expect well-capitalized banks to react more intensively than highly leveraged banks.

In this respect the most significant contribution of this paper is to bring evidence of this heterogeneity in banks' response to deposit insurance adoption. First, I find that relative size and systemicity of banks are positively and significantly related to banks' responsiveness to introduction of deposit insurance. For the most systemic banks, i.e. those belonging to the top 10%/top 5% of the distribution within a country, deposit insurance adoption has no significant impact on leverage. This finding is consistent with the view that systemically important banks already benefit from implicit state guarantees so that they are unaffected by the introduction of an explicit system of deposit insurance. Accordingly, deposit insurance adoption could have important *competitive effects* by removing the comparative advantage of large and systemic banks and by improving competition on the banking market. Second, I provide evidence that banks' response to deposit insurance adoption is an increasing function of their initial leverage so that only the least leveraged banks react to implementation of explicit deposit guarantees. The results indicates that the 20% most highly leveraged banks before adoption do not change their capital buffer after implementation of deposit insurance. We thus observe a *convergence process* in terms of capital buffer across banks: the whole banking system is less well-capitalized and thus less resilient to large shocks.

From a methodological point of view, this paper examines the effect of deposit insurance adoption by using essentially a *differences-in-differences* methodology. Identification relies on comparisons of the changes in risk-taking over time between banks in countries that adopted a deposit insurance scheme at a given date and banks in countries that did not. There are potential estimation concerns that are carefully addressed. First, a correct identification of the effect relies on the common trends assumption. If the trends of the treatment and control groups differ in a systematic way, the estimated treatment effect is unidentified. I address this issue by adding linear and quadratic country-specific trends and by replicating the results on a sample using a different control group. Second, decision to adopt deposit insurance is likely to be endogenous: an increase in bank risk-taking can significantly raise the demand for insurance by depositors and put governments under pressure to adopt a deposit insurance scheme. I carefully consider this reverse causality issue by running falsification tests and placebo analysis. Third and most importantly, I investigate the possibility that deposit insurance adoption comes with simultaneous changes in financial regulation or with some country-specific aggregate shocks like banking crises. I check that the results are not affected by taking into account banking crisis episodes and by controlling explicitly for changes in banking regulation.

The remainder of this paper is organized as follows. The second section offers a brief presentation of deposit insurance schemes in which I discuss the main costs and benefits associated with the implementation of deposit insurance scheme. In the third section, I present the data. I provide a short graphical and statistical analysis in the fourth section. In the fifth section, I present the identification strategy. I then set forth the results in the next section. The seventh section consists in robustness checks. The last one concludes.

2 Deposit Insurance Scheme: a Brief Presentation

The first deposit insurance scheme in the world was the Federal Deposit Insurance Corporation (FDIC) in the United States.[3] The decision was taken just after the wave of bank failures experienced during the Great Depression. On June 16, 1933, President Roosevelt signs the Banking Act (also known

[3] In Norway there was a guarantee fund for savings banks with voluntary membership as early as 1921 which then became mandatory in 1924, whereas a guarantee fund for commercial banks was first introduced in 1938. However, Norway's guarantee fund is not considered a pure deposit insurance scheme so it had no official explicit deposit insurance until 1961. (Demirgüç-Kunt et al. (2008) and EFDI 2006 report)

as the Glass-Steagal Act) "*creating a Federal Deposit Insurance Corporation and providing for the insurance of deposits in member banks of the Federal Reserve System and also in nonmember banks under certain conditions.*".[4] The temporary scheme was fully implemented on January 1, 1934 and the Banking Act of 1935 established the FDIC as a permanent agency of the government. The explicit goal was to raise the confidence of the Americans in the banking system by alleviating the disruptions caused by bank failures and bank runs.[5]

Since then, a large number of countries have adopted an explicit deposit insurance scheme as part of their regulatory framework.[6] Establishment of deposit insurance schemes has been largely promoted by IMF and World Bank in the 90's. Similarly, a deposit insurance scheme is now required to become member of the European Union. These last years, an international harmonization of these deposit insurance schemes has been initiated by the *International Association of Deposit Insurers* and the *European Forum of Deposit Insurers*, both founded in 2002. In 2010, 109 countries have an explicit deposit insurance system.

Protecting small and unsophisticated depositors with deposit insurance has the main advantage of ruling out bank runs and panics in case of financial stress or lack of confidence in the banking system. When depositors are uncertain about the liquidity position of their bank, the best individual strategy is to run withdrawing their funds from bank. However, this strategy is collectively inefficient because it forces banks to stop profitable projects and to sell assets at fire-sale prices, which may destabilize the entire banking system because of contagion (Allen and Gale (2000) and Diamond and Rajan (2005)).[7] These contagion phenomena can lead to a drastic reduction in the amount of loans offered to the economy for an extended period of time. Deposit insurance is a powerful tool to remove this uncertainty so that there is no longer room for panics and inefficient bank runs (Diamond

[4] http://archive.org/details/FullTextTheGlass-steagallActA.k.a.TheBankingActOf1933

[5] See http://www.fdic.gov/bank/historical/brief/brhist.pdf for further details on the history of the FDIC

[6] Countries having an explicit deposit insurance scheme and years of adoption are presented in table 1.

[7] Nonetheless, some work show that bank runs can be seen as a way to introduce some contingency in demand deposit contract. Accordingly bank runs can be efficient. See Allen and Gale (1998).

and Dybvig (1983)). This is definitely the main benefit from introducing an explicit deposit insurance scheme as shown by the recent financial crisis. Just after the Lehman fall, there were large doubts about the health of many banks. But no banks really faced a bank run by non-institutional depositors, excepting Northern Rock. It is also very likely that some bank liquidations have been facilitated because depositors didn't run even though failure was almost certain.

However, deposit insurance schemes may have significant adverse effects. It is often argued that deposit insurance reinforces moral hazard in banking: existence of deposit insurances makes depositors less interested in monitoring bank risk-taking. In other words, deposit insurance sensibly erodes market discipline as evidenced by Demirguc-Kunt and Huizinga (2004). Then, shareholders and bank management can keep any excess profits without having to support the cost of excessive risk-taking on deposit rates (Merton (1977)). This relaxation of market discipline is very likely concerning the bank leverage, i.e. the bank capital buffer. In presence of guarantees, creditors are much less concerned by the capital cushion of banks. Banks can thus improve the return on equity by increasing their leverage. Overall, there are strong presumptions that introduction of a deposit insurance scheme may foster bank risk-taking if deposit insurance premia are not adequately priced.[8]

Accordingly, most of deposit insurance schemes are designed to limit these perverse incentives. First, there often exists upper bounds on the amount covered (100 000 € in the euro zone for instance). These limits make possible to discriminate between small, fragile, and uninformed depositors from large depositors who are supposed to have higher ability to monitor banks as shown by Ioannidou and Penas (2010). Also, many deposit insurance schemes incorporate a *coinsurance mechanism*. In this case, depositors will have to support a small share of the losses in case of bank failure. Another way to curb the moral hazard related to deposit insurance can be to implement *risk-based* premium rather than *flat* premium: the more risky the bank strategy, the higher the premium the bank have to pay. But it requires to very accurately assess the ex ante risk of banks, which can be difficult

[8] That is exactly what Keeley (1990) explained in the introduction of his famous paper: *"It has long been recognized that a fixed rate deposit insurance system, such as the Federal Deposit Insurance Corporation's (FDIC's), or the Federal Savings and Loan Insurance Corporation's (FSLIC's) can pose a moral hazard for excessive risk taking. The reason is that banks or thrifts can borrow at or below the risk-free rate by issuing insured deposits and then investing the proceeds in risky assets with higher expected yields."*

(Acharya et al. (2010)). More generally, deposit insurances schemes have various features that may induce some heterogeneity in the effects of these guarantee funds on bank risk-taking.[9]

To summarize, the main benefit associated with deposit insurance is to rule out inefficient and very destructive bank runs. This is why deposit insurance scheme has been largely promoted across the world by various institutions like the IMF or the World Bank. However, in providing guarantees on the liabilities of banks, it can fuel bank risk-taking and make more likely to experience bank failures. The next sections aim to assess precisely these cost associated with deposit insurance adoption, namely the increase in risk-taking following introduction of deposit insurance through the reduction of capital buffer.

3 Data

3.1 Sources and Construction

This paper uses two distinct databases. The first one is the *Fitch IBCA's BankScope* database widely recognized as the most important banking database in the world. It provides detailed balance sheets of banks in most countries over the last twenty years. Second, I construct a new data set by reviewing and updating the existing databases about deposit insurance schemes. Especially, for each country I collect rigorously the year of adoption of the deposit insurance scheme. The data, the sources and the exact procedures implemented are described extensively in the appendix A.

The restrictions imposed on the data set are also detailed in the appendix A. In particular, I choose to keep the largest set of countries as possible by including those having already adopted a deposit insurance scheme before banking data started to be collected (like USA or Germany for instance). The estimates of the effect of deposit insurance adoption should not be affected directly by observations from these countries. But these observations enlarge the control group used in the estimation process helping to smooth its size and its composition over time. To strengthen the validity of the results, I also perform the regressions on a sample restricted to countries adopting a

[9] But collecting time-varying data about these features is a hard task. See Appendix A for further discussion on this issue

deposit insurance during the period covered.[10] I will come back to this issue when discussing my estimation strategy.

Ultimately, the main sample consists in a database with bank-level balance sheet information over the years 1986-2011 for 117 countries. For 68 of them, a deposit insurance scheme is implemented during a period for which we have bank balance sheet information. The database contains 207 060 bank-year observations and 18 825 unique banks.[11] On average a bank has 12 years of observations, with a minimum of 5 years and a maximum of 16 years. Among these 117 countries, 86 have an explicit deposit insurance scheme. For each country, the exact year of adoption and the number of banks are presented in table 1.

I face two important issues with this sample. The main difficulty arises from the increasing coverage over time: the number of banks within a country and the number of countries reported in BankScope increases sensibly over time, especially during the first years i.e. between 1986 and 1999. This is an important weakness that can affect the results and it is an important motivation for using bank fixed-effects. Second, as explained in the previous section, there are some heterogeneity in the deposit insurance characteristics across countries (upper bound, coinsurance mechanism, nature of the premia...). Unfortunately, I cannot control explicitly for these time-varying features by lack of information as explained in the appendix A. I can only control for the time-invariant or slow-moving dimension of these characteristics with bank fixed-effects. Therefore, the main objective of this study is to evaluate the risk-shifting effect of deposit insurance that is independent of the characteristics of the deposit insurance schemes. I argue that adoption itself is likely to have the largest effect on bank risk-taking while the various features may only impact marginally this initial adverse effect.

3.2 Bank Risk Measurements

This paper aims to provide a new look on the effects of a specific regulatory change –the introduction of a deposit insurance scheme– on bank risk-taking,

[10] 1986-2011

[11] First, note that 9 935 (almost 54% of the sample) are US banks (112 286 obs.) and 2 215 (almost 13% of the sample) are German banks (27 762 obs.). Second, among these 207 060 bank-year observation, 1 477 have missing log-transformed risk proxy because of negative value. I keep them because I run robustness check using risk-proxy without log-transformation.

with a particular focus on the leverage. Before presenting the indicators used, I discuss briefly the data limitations. First, the database used consists in balance-sheet of banks, and only few of these banks are listed.[12] Hence, market-based measurements are not used in this paper and only balance sheet measurements of risk are taken into consideration. Second, Tier 1 and Total risk-weighted capital ratios are missing for almost all banks from countries other than USA.[13] Hence the leverage ratio used in this paper is the Capital-to-Assets ratio, i.e. the ratio of equity over total unweighted assets. But there are also more fundamental reasons to focus on the Capital-to-Assets ratio.

While a preference toward a regulation based on risk-weighted leverage measures has been observed these last twenty years, the recent financial crisis has also stressed the importance to monitor raw leverage ratios. For instance, Basel III agreements will introduce "*a simple, transparent, non-risk based leverage ratio that is calibrated to act as a credible supplementary measure to the risk based capital requirements*".[14] This ratio will help to "*constrain the build-up of leverage in the banking sector, helping avoid destabilizing deleveraging processes which can damage the broader financial system and the economy*" by introducing "*additional safeguards against model risk and measurement error*". The recent crisis has shed light on the limits of the regulation based on risk-weights (Acharya et al. (2012)) and regulators now recognize the importance to also monitor raw leverage ratio of banks.

I also investigate the effect of deposit insurance on individual probability of default by using the (log of) z-score as dependent variable. This increasingly popular measure of bank risk-taking[15] is computed as the sum of the *Capital-to-Assets Ratio* (CAR_t) and the average *Return on Average Asset* ($ROAA$) over the standard deviation of $ROAA$ for a given period :

$$Z_t = \frac{\mu(ROAA_t) + CAR_t}{\sigma(ROAA_t)}$$

One important advantage of the z-score is to combine the leverage risk with two additional dimensions of risk: the profitability and the volatility of returns. Formally, the z-score measures the individual probability of insol-

[12] Only 904 banks corresponding to 10 823 obs. are listed.

[13] Tier 1 ratio is missing for 77 292 observations over 94 774 (81%)

[14] http://www.bis.org/publ/bcbs189_dec2010.pdf

[15] Beck (2008),Laeven and Levine (2009), Demirgüç-Kunt and Huizinga (2010), Beck et al. (2011) for instance

vency (Boyd and Runkle (1993)).[16] It reflects the distance-to-default i.e. the number of standard deviations that a bank's $ROAA$ has to fall for the bank to become insolvent for a given leverage ratio. The higher the z-score, the lower the risk of default. Additional information about the z-score can be found in appendix.[17]

4 Graphical and Statistical Analysis

Before discussing the identification strategy and the econometric results, I present some graphical evidence that deposit insurance adoption can be suspected to increase both leverage and probability of default. I start by presenting the evolution of both indicators across time. It is important to figure out what is the global trend of these outcome variables because identification of the effect of deposit insurance adoption relies on time-series comparisons.

In figures 1 and 2 , I plot the evolution of the average and the median values of both risk measurements. The sample is restricted to banks facing deposit insurance adoption to be more in line with the econometric analysis: it excludes banks that are not used to identify the effect of adoption. This restriction is mainly motivated by the fact that BankScope suffers from an artificial trend in coverage that could distort the results. We observe that both the Capital-to-Assets ratio and the log of z-score tend to increase over time (or at least to be flat). For instance, the average (median) value of the Capital-to-Assets ratio raises from 10% (6%) in 1990 to 15% (11%) in 2002 before stabilizing around 13% (11%). The only notable exception concerns the average Capital-to-Assets ratio during the years 2002-2005 and 2009-2011 during which it is slightly decreasing. From these figures, we conclude that the effect of deposit insurance adoption that we capture in this paper –a downward shift of both the capital buffer and the distance-to-default– is at odds with the global trend observed these last 20 years.

[16]Defining insolvency as the state in which capital is fully depletes by negative returns on asset, i.e. $CAR_t + ROAA_t < 0$, the probability of insolvency is defined as $P[ROAA_t < -CAR_t]$. Then a simple application of the Bienaymé-Chebyshev inequality provides an upper bound of this probability (with strict equality if $ROAA_t$ is normally distributed) :

$$P[ROAA_t < -CAR_t] \leq Z_t^{-2}$$

[17]To make both risk measurements homogeneous, I multiply the log of z-score by -1 such that lower values of log of z-score are now associated with higher insolvency risk.

By comparing the distribution of both the log of z-score and the Capital-to-Assets ratio before and after deposit insurance adoption, we can now figure out more precisely the possible effect of deposit insurance adoption. We want to know whether we observe a systematic shift in the distribution after deposit insurance implementation that could indicate an increase in bank risk-taking. Note that we continue to restrict the sample to banks having observations before and after the introduction of deposit insurance adoption. The figures 3 and 4 represent these two distributions. In both cases, we observe clearly a left shift in the distribution of risk after the implementation of deposit insurance. This indicates a decrease in both the Capital-to-Assets ratio and the distance-to-default, that is to say an increase in bank risk-taking. For instance in figure 3, we have much less very highly capitalized banks (i.e. those with a Capital-to-Assets ratio above 20%) and much more highly under-capitalized banks (i.e. those below 10%) after deposit insurance adoption. Figures 1 and 2 in appendix show the kernel density estimates of these distributions. Kernel density estimates have the advantages of being smooth and of being independent of the choice of origin. The previous conclusions are entirely confirmed by these figures.

However, when there are much more observations per banks after adoption than before, these distributions are biased. To overcome this issue, I compute the average value before and after adoption for both risk-taking indicators. Then, I keep only one observation per bank and per period, i.e. one observation before and one observation after adoption, and I plot the distributions of these average values. These are the figures 4 and 5. The previous conclusions are strengthened by this additional restriction. We continue to observe a shift toward the left of the distribution after deposit insurance adoption denoting an increase in risk-taking. In the figures 3 and 4 in appendix, I present the distribution of the difference in the average values of risk before and after adoption for each banks. Distributions with a large mass of negative values would be evidence in favor of the risk-shifting effect of deposit insurance adoption. It would indicate that a large fraction of banks have lower average Capital-to-Assets ratio or lower average distance-to-default after adoption. This is exactly what I find: both distributions are highly skewed toward negative values.

Finally, I report descriptive statistics for the leverage and the distance-to-default before and after deposit insurance adoption in table 3. For both measurements, we have additional evidence that deposit insurance is likely to have a negative effect on risk-taking. The average (resp. median) Capital-to-Assets ratio decreases by 6.7% (9.1%) and the average (resp. median) log of z-score decreases by 5.7% (5.9%). Thresholds corresponding to the 25th and 75th percentile also denote an increase in risk-taking. According to these simple descriptive statistics, banks are less capitalized and more likely to default after the adoption of deposit guarantees.

In conclusion, this graphical and statistical analysis offers preliminary evidence that deposit insurance adoption is very likely to induce an increase in both the leverage ratio and the probability of default. To confirm this intuition, I conduct an econometric analysis. I explain the identification strategy and I present the results in the next section.

5 Identification Strategy

The primary goal of this paper is to assess over a large panel of banks the impact of deposit guarantees on bank leverage. The identification uses essentially a differences-in-differences methodology. From the database on *Deposit Insurance Schemes,* I construct a dummy taking the value of one after a deposit insurance was introduced in a given country and zero before. This is the main independent variable of interest. Define $\hat{t}_j$ as the year in which a deposit insurance has been implemented in country j gives :

$$DI_{j,\,t} = \begin{cases} 1 & if\ t \geqq \hat{t}_j \\ 0 & if\ t < \hat{t}_j \end{cases}$$

The baseline regression performed is the following :

$$Risk_{i,j,t} = \alpha + \beta \cdot DI_{j,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \tag{5.1}$$

where i denote the bank, t the year and j the country. $Risk_{i,j,t}$ stands for the different risk-taking proxies considered. $X_{i,t,j}$ is the vector of control variables, θ_t are year fixed-effects and u_i are bank fixed-effects. Standard errors are clustered at the country-level. The main coefficient of interest is β, the effect of introducing a deposit insurance scheme on bank risk-taking. The identification of β relies on the comparison of the changes in risk-taking over time between banks in countries that adopted a deposit insurance scheme *at a given date* and banks in countries that did not. The staggered passage of the deposit insurance means that the control group is not restricted to countries that never adopt a deposit insurance scheme. In fact, the identification implicitly takes as the control group all banks operating in countries that do not adopt a deposit insurance scheme at time t, even if they have already adopted a deposit insurance or will adopt one later on.

Compared with previous work, this paper focuses on the *within-bank* effect of deposit insurance adoption. Using bank fixed-effects u_i has several advantages. First it allows to exploit substantial additional variability by adding time-series dimensions of the data. It is also a way to control for time-invariant unobserved heterogeneity at the bank level.[18] Recent work have stressed that fixed-effects explain most of the variation in leverage, for both corporate firms and banks (Lemmon et al. (2008) and Gropp and Heider (2010)).

But, an important benefit from using bank fixed-effects is more directly related to the issue investigated. Deposit insurance adoption can have two distinct effects on bank risk-taking and it is important to consider them separately. First, it can increase risk-taking for existing banks: this is the intensive margin effect. Second, it can promote the entry of riskier banks: this is the extensive margin effect. Using bank fixed-effects permits to focus on the intensive margin effect. Naturally, distinguishing these two effects is important. But this approach is even essential given the increasing coverage of BankScope. From 1985 to 2000, the number of banks reported in a given country and the number of countries covered tends to increase continuously in the sample. It is thus very difficult to assess the extensive margin effect because the results could be largely driven by these artificial changes in coverage. To my knowledge, this paper is one of the first to consider seriously this issue.[19]

Other time-varying factors could also affect the choice of banks leverage. If these factors vary precisely at the time of deposit insurance adoption, it could produce spurious correlations. To overcome this issue, it is possible to include time-varying control variables. However, any covariates included as control variable must be unaffected by the treatment (Roberts and Whited (2011)). This condition severely limits the possible covariates to include. For instance, size is generally considered as an important determinant of

[18] Kalemli-Ozcan et al. (2011) detail various bank-level or country-level time-invariant differences that are accounted for by using fixed-effects. Among them are accounting practices, balance sheet representation and domestic regulatory adjustment. As explained previously, in the present situation it also controls for any time-invariant differences in the feature of the deposit insurance schemes.

[19] The recent paper by Kalemli-Ozcan et al. (2011) also shed light on this important issue.

leverage structure but it is also very likely to be affected by deposit insurance adoption. Hence, I only consider a restricted set of control variables and I report all the results both with and without these covariates.[20]

The first control is the *real GDP annual growth rate* as the business cycles are one of the major source of fluctuation in the riskiness of bank's balance sheet. Then the *inflation rate* is included in the set of controls as a traditional determinant of bank risk-taking. In order to control for the degree of financial development, the *logarithm of GDP per capita* is included in the vector of controls. They are all obtained from the World Bank statistics over the period 1985-2011. Moreover, an important debate exists about the impact of concentration on bank risk-taking.[21] In any case, market structures like concentration are largely considered as an important determinant of bank risk-taking. Using market shares on the deposits market, an *HHI index* is constructed for each country, measuring the concentration on the deposit market.[22] Recall that

$$HHI_t = \sum_{i=0}^{n} (MarketShare_{i,\,t})^2$$

where n is the total number of banks on a specific market. A higher *HHI index* denotes a more concentrated deposits market. Finally, the inclusion of year fixed-effects in the regressions allow to control for aggregate fluctuations. In the next section, I will present and discuss the results.

6 Results

6.1 Baseline specification

In this section, I present and discuss the results from the baseline specification (5.1). A negative and significant value for $\hat{\beta}$ means that on average banks tend to be more leveraged after the introduction of a deposit insurance scheme than before. Results are reported in table 4. The first two columns report regressions with only year fixed-effects and bank-fixed effects. Each regression is estimated with robust standard errors clustered

[20] Regressions using a larger set of covariates, notably bank level controls, can be found in the appendix.

[21] See Boyd and De Nicolò (2005) for an overview

[22] Correlation between HHI on the loans market and HHI on the deposits market is 0.95. It doesn't make any differences to use the one or the other.

at the country-level to correct for within-country serial correlation (Petersen (2009)). Nonetheless, correct estimation of standard errors is challenging in a difference-in-difference framework. This is why I also implement the method proposed in Bertrand et al. (2004) to address serial correlation issues in the robustness checks section.

The first two columns of table 4 show the basic impact of deposit insurance adoption on bank risk-taking without any controls. We observe an important and a very significant negative effect, meaning that banks tend to increase their leverage after the implementation of deposit insurance scheme. I then add the set of controls variables. The coefficients on deposit insurance adoption keep the same sign and magnitude, as well as they remain highly significant for both risk proxies.

There are different ways for interpreting the economic significance of these coefficients. First the effect can be interpreted directly in terms of percentage change. Concerning the Capital-to-Assets ratio, the estimated coefficient indicates that the leverage of banks tends to decrease by 15.33% after deposit insurance adoption.[23] In the case of the log of z-score, adopting a deposit insurance scheme tends to reduce the z-score by 16.52%.[24]

It is also possible to interpret these results in a different way. Irrespective of the percentage changes in the level of risk-taking reflected by these two proxies, it is worth to know how these changes in risk-taking following deposit insurance adoption compare to "natural" fluctuations of risk-taking. Precisely, I want to relate the magnitude of these effects to the sample *within* standard deviations of the two risk-taking measurements. In table 3, I report the *overall*, *between* and *within* standard deviation of both the log of z-score and the Capital-to-Assets ratio computed on the sample of banks on which the effect of deposit insurance adoption is estimated. It appears that the implementation of a deposit insurance scheme produces an increase in risk-taking corresponding to 31.79% of one sample within standard deviation for the Capital-to-Assets ratio and 44.73% of one sample within standard deviation for the log of z-score. [25]

[23] This is the magnitude of the effect evaluated at the mean of the sample on which the deposit insurance dummy is estimated: $-0.0230/0.15$. The magnitude of the effect becomes 20.91% when evaluated at the mean of the full sample: $-0.0230/0.11$.

[24] This value is computed as follow $100 \cdot [exp(c^* - \frac{1}{2} \cdot v^*(c^*)) - 1]$, where c^* is the estimated coefficient and $v^*(c^*)$ is the estimated variance of c^* as suggested by Kennedy (1981).

[25] These are the *in-sample* magnitudes of the risk-shifting effect of deposit insurance. When comparing with the within standard deviation computed over the entire sample

These results hence suggest that there exists a negative and significant correlation between the implementation of a deposit insurance scheme and the bank financial soundness. This relation appears to be mainly driven by a rise in the leverage ratio: we capture an increase of 15% in the leverage ratio of banks after deposit insurance adoption. This finding is consistent with the literature (Keeley (1990), Berger et al. (1995), Saunders and Wilson (1999), or Acharya et al. (2011)).

Bank creditors are particularly concerned by monitoring the amount of equity held by the bank. First it is the capital cushion that is intended to absorb unexpected losses: the lower the Capital-to-Assets ratio, the more fragile the bank in case of unexpected shocks. Second, a higher level of Capital-to-Assets ratio signals that banks has more *skin in the game* and thus less incentives to make risky investment. In presence of deposit insurance, depositors become much less concerned by the bank Capital-to-Assets ratio because of the guarantees offered (as shown by Demirguc-Kunt and Huizinga (2004) or Nier and Baumann (2006)). After deposit insurance adoption, banks being no longer charged for excessive risk-taking, shareholders and management have strong incentives to reduce their Capital-to-Assets ratio to increase the return on equity for a given return on assets. The adverse impact of deposit insurance on bank leverage is actually largely recognized: "*Indeed, the entire system of capital regulation is the result of the recognition that incentives to take excessive risk arise as a result of demand deposit and other elements of the safety net of banks.*" (Admati et al. (2011)).

Compared with the previous work of Gropp and Vesala (2004), this paper isolates the intensive margin effect, that is to say the change in leverage for existing banks. It is crucial because the identification is otherwise contaminated by the artificial changes in BankScope coverage. Moreover, their identification of the effect of deposit insurance relies on time-series variation in only 4 European countries while I am using variation in deposit insurance scheme in almost 54 countries. This finding also challenges the results established by Gropp and Heider (2010). The authors find that bank leverage is insensitive to deposit insurance *coverage*. Two reasons may explain these contrasting results. First, they focus on large banks of developed countries while I am working mainly with banks in developing countries irrespective of

(and not just on the sample of banks on which the effect of deposit insurance adoption is estimated), the *out-sample* magnitudes become much larger: 49.59% (0.0230/04638) for the Capital-to-Assets ratio and 60.94% (0.1797/0.2949) for the log of z-score.

their size. Second, their identification strategy is based on variations in deposit insurance coverage across countries. It is possible that the introduction of an explicit deposit insurance scheme sends an important signal to depositors and banks whereas variability in deposit insurance coverage is likely to be less noticeable explaining why these variations generate less differences in banks behavior.

Overall these results exhibit some evidence that adopting a deposit insurance scheme fosters risk-taking by reducing the capital buffer of banks by 15%. Before turning to the most important part of this paper investigating the heterogeneous effects of deposit insurance adoption, I want to discuss three potential identification issues.

6.2 Tests of Identification Strategy

The results established in the previous section seem to indicate that deposit insurance adoption makes banks much more leveraged. Nonetheless, the identification strategy summarized in equation (5.1) may suffer from three problems. The first one concerns *the common trends assumption*: to conclude that the changes in leverage observed are *caused* by deposit insurance adoption, we have to assume that in the absence of deposit insurance adoption, the leverage ratio and the distance-to-default would have evolved similarly between treatment and control groups.

Second, the identification strategy may face a reverse causality issue. Indeed, we could suspect that bank leverage starts to increase before deposit insurance adoption. This increase in bank leverage can then raise the demand for insurance by depositors and force the government to adopt a guarantee scheme. In this case, the coefficient estimated by equation (5.1) captures the effect of an increase in bank risk-taking on the probability to adopt a deposit insurance rather than vice versa.

Third and most importantly, identification may suffer from a simultaneity bias. It is possible that we also capture the effect of another change in banking regulation occurring at the same time as the deposit insurance implementation. Similarly, it is hard to separate out the effects of country-specific shocks contemporaneous with the deposit insurance adoption from the effects of the deposit insurance adoption itself. In particular, countries may adopt a deposit insurance scheme precisely at the time where they suffer from a severe financial crisis. To address this issue, I control explicitly for the effects of regulatory changes and those of banking crises by using the data from Abiad et al. (2010) and Valencia and Laeven (2008).

6.2.1 Common Trends Assumption

It is quite difficult to test the common trends assumption, especially in a context in which the implementations of the law are staggered over time. One immediate solution relies on the inclusion of country-year interactions terms. While completely nonrestrictive, such a specification is not possible in the current framework.[26] However, the inclusion of country-specific trends in the baseline regressions is an alternative solution allowing the outcome of treatment and control groups to follow different trends in a limited but potentially revealing way (Angrist and Pischke (2008)).

Since I do not have any prior about the shape of these potential country-specific trends, quadratic trends are also included in the regressions allowing for a more flexible specification. In this case, the effect of deposit insurance is identified from a break in the pattern of bank's risk-taking that is distinguishable from a smooth quadratic. The regressions estimated are the following:

$$Risk_{i,j,t} = \alpha_i + \beta \cdot DI_{j,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \sum_j \tau_{lin.} \cdot Trend_{j,t} + \epsilon_{i,j,t} \tag{6.1}$$

$$Risk_{i,j,t} = \alpha_i + \beta \cdot DI_{j,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \sum_j \tau_{lin.} \cdot Trend_{j,t} + \sum_j \tau_{quad.} \cdot Trend^2_{j,t} + \epsilon_{i,j,t} \tag{6.2}$$

Results are reported in tables 6 and 7. All the previous conclusions remain largely unchanged even after taking into account country-specific trends. The deposit insurance variable keeps the expected signs in both regressions and the significance remains the same. While slightly lower, the magnitude of the effect is mostly unchanged for both measures. To sum up, controlling for country-specific trends does not alter the initial findings. An alternative way to check the sensitivity of the results to the common trends assumption

[26] Because it is no longer possible to estimate the deposit insurance dummy which is country-year specific.

consists in using a different control group. Finding different results should be a source of concerns. I run such a sensitivity test in the robustness checks section and the conclusions are unaltered. It is thus unlikely that treatment and control groups experience different evolutions of leverage ratio in such a way that it could contaminate our identification of the effect of deposit insurance adoption.

6.2.2 Reverse Causality

Another potential issue is that we cannot exclude a priori that deposit insurance schemes are implemented in a country after bank risk-taking starts to increase significantly. A change in bank leverage observed by depositors can increase pressures on government to adopt a system of deposit guarantees. Alternatively, growing international competition may force banks to take more risk and then to lobby for implementing a deposit insurance scheme preserving them from paying excessive deposit rates. In both case, the baseline identification strategy may suffer from a reverse causality issue. To rule out this possibility, I implement a falsification test.[27]

For this purpose, I replace the main deposit insurance dummy variable by a set of dummy variables taking the value of one exactly τ years after or τ years before the true adoption :

$$\begin{cases} DI^{Before}_{j,\hat{t}_j-\tau} = 1 & if\, t = \hat{t}_j - \tau \\ DI^{After}_{j,\hat{t}_j+\tau} = 1 & if\, t = \hat{t}_j + \tau \end{cases}$$

where $\hat{t}_j$ denotes the year of adoption in country j. Then I run the following regression :

$$Risk_{i,j,t} = \alpha_i + \beta \cdot DI_{j,t} + \sum_{\tau=1}^{6} \lambda_\tau \cdot DI^{Before}_{j,\hat{t}_j-\tau} + \sum_{\tau=1}^{7} \lambda_\tau \cdot DI^{After}_{j,\hat{t}_j+\tau} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \quad (6.3)$$

With this specification, it is possible to assess whether an increase in risk-taking is observed in the years preceding the deposit insurance adoption. In this case, some dummy variables for the year before the true adoption should have a negative and statistically significant coefficient. Finding such an effect would be symptomatic of potential reverse causality.

[27] Angrist and Pischke (2008) and Roberts and Whited (2011). See Gruber and Hungerman (2008) for an application.

The results can be found in table 8. The first two columns shows the results from a specification in which the reference year is set to be the year preceding adoption.[28] We observe that the dummy variables for the years *preceding* adoption are never significantly different from zero and have very low magnitude compared to the one of the effect previously found. In contrast, all the dummy variables associated with the year *following* adoption present a negative and highly significant effect. These results indicates that both the leverage ratio and the distance-to-default have regular patterns before adoption: we cannot find any jump in bank risk-taking before adoption.[29] The leverage ratio or the distance-to-default start to decrease significantly only after the adoption.

The next two columns investigates a slightly different specification. Now, I include a dummy for all the periods around the adoption year.[30] This specification is more in line with those from Autor (2003) or Bertrand and Mullainathan (2003). Additionally, I perform a placebo analysis in simulating "false" deposit insurance adoption. The exact method and the results are presented in the appendix B. The conclusions remain the same: there is no evidence that risk-taking starts to increase significantly before adoption. These specification checks tend to reject the possibility of reverse causation driving the baseline results.

6.2.3 Simultaneity

The most important concerns about the identification strategy relates to the possibility that deposit insurance adoption comes with other changes in financial regulation or with some country-specific aggregate shocks like banking crises (Demirgüç-Kunt et al. (2008) and Demirguc-Kunt and Detragiache (2002)). To tackle this issue, I use the data collected by IMF researchers (Abiad et al. (2010) and Valencia and Laeven (2008)) concerning banking crises and financial reforms across the world. The banking crisis database provides the starting date and the ending date of 42 crisis episodes in 37

[28] The graphical representation of this specification can be found in figures 7 and 8.

[29] A source of concerns could be the downward trend that we can observed by looking at figures 7 and 8. In both cases, the risk-taking tends to slightly increase with time. However, we clearly identify a significant break in this downward trend exactly at the time of adoption: bank risk-taking increases much more than what we could have expected according to this long term trend.

[30] Note that the reference year is no longer explicitly defined.

countries. I thus construct a dummy variable $Crisis_{j,\,t}$ taking the value of one for each crisis episode. The financial reforms database covers 91 countries over 1973-2005. It provides various index of financial reforms including an index relative to prudential regulations and supervision of the banking sector which are the kind of reforms the most likely to affect the leverage ratio of banks. This indicator sums up four distinct dimensions and takes values between 0 and 3 in which higher values denote more regulated banking sectors.[31]

Based on these two indicators, I run the following regressions aiming to control for simultaneous changes in regulation and banking crises:

$$Risk_{i,j,t} = \alpha + \beta \cdot DI_{j,t} + \omega \cdot Crisis_{j,\,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \tag{6.4}$$

$$Risk_{i,j,t} = \alpha + \beta \cdot DI_{j,t} + \omega \cdot Reform_{j,\,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \tag{6.5}$$

We expect a positive coefficient for the financial reform indicators and a negative coefficient for the banking crisis dummy. In the case in which the effect of deposit insurance partially captures the effect of simultaneous changes in regulation and banking crises we should observe a large reduction in the magnitude (and possibly in the significance) of the coefficient for the deposit insurance dummy. Results of theses regressions are presented in table 9. The first two columns replicates the baseline results. The third and the fourth columns present results including the banking crisis dummy while the fifth and the sixth columns show the results after adding the banking supervision index. In both case, the coefficient for each indicator is insignificant. Above all, their economic significance is very small: the magnitude of the coefficient associated to banking crisis and banking supervision is almost 10 times smaller than the coefficient of deposit insurance adoption. In columns 7 and 8, I replace the banking supervision index by the overall financial reforms index.[32] Results indicates that financial liberalization seems to be positively related to bank risk-taking but the inclusion of this indicator in the set of regressors is without any effect on the estimated impact of deposit insurance adoption. Finally, in columns 9 and 10 I present results of regressions using both indicators simultaneously.

[31] Note that the limited time coverage of this indicator reduces the sample size. To keep sample size similar across regressions, I assign the value of the year 2005 to the financial reform indicator for the years 2006-2011.

[32] This index aggregates seven dimensions to obtain a single liberalization index for each economy and for each year.

The most important message from these regressions is that the economic and statistical significance of deposit insurance adoption is only marginally affected by inclusion of these indicators: the maximum diminution corresponds to 9% of the magnitude of the effect while statistical significance is unchanged. Finally note that bias related to simultaneous changes in banking regulation, if present, is likely to be a downward bias. These last twenty years, the regulatory framework of banking activities has been more directed toward higher capital ratio than the opposite as evidenced by the successive implementation of Basel I and Basel II.[33] It is even possible to think that such simultaneous regulatory changes could be designed to mitigate the perverse effect of deposit insurance adoption. Hence, regulatory changes implemented at the same time as deposit insurance are likely to induce an increase in the Capital-to-Assets ratio going against the expected effect of deposit insurance adoption.

To summarize, the identification strategy does not seem to suffer from simultaneity: even after taking into account banking crisis and changes in banking regulations, the effect of deposit insurance remains mostly unchanged. After having considered carefully the potential biases that could affect the baseline results, we can turn to the most important contribution of this paper.

6.3 An Analysis of the Heterogeneity of Banks' Response : the Competitive Effects of Deposits Insurance Adoption

The results presented in the previous sections demonstrate that deposit insurance adoption adversely impacts banks' capital buffer. The theory predicts that deposit insurance should relax the market discipline from depositors. Accordingly, banks have strong incentives to adopt more risky behaviors because creditors no longer price efficiently these risky strategies. In particular, we expect that banks would operate with much lower Capital-to-Assets ratio in presence of deposit insurance. Consistent with these predictions, I find that deposit insurance adoption reduces the capital buffer of banks by 15%. This increase in the leverage ratio of banks translates into lower distance-to-

[33] At least in the countries on which the effect of deposit insurance adoption is estimated, that is to say mainly developing countries. This is exactly what we observed in the figures 1 and 2

default, that is to say higher probability of failure.

However the effect identified previously is an *average effect* across the whole sample of banks and it is quite plausible that adopting a deposit insurance should have heterogeneous effects on banks along various dimensions. For instance, number of authors suggest that deposit insurance should benefit mainly to small banks (Calomiris and White (1994), Demirguc-Kunt and Kane (2002) and Demirgüç-Kunt et al. (2008) for instance). From the regulators perspective, it is very important to improve its knowledge about the heterogeneity in banks' response and to identify which banks react the most to deposit insurance adoption. The present section investigates these likely heterogeneous responses of banks.

The main conclusion is that deposit insurance has important competitive effects on the banking industry: adoption of deposit insurance scheme seems to benefit mostly to small, non systemic and well-capitalized banks. First, I find that banks' response to the introduction of deposit guarantees is more important for banks with *small initial market shares*. Similarly, the response of banks to deposit insurance adoption is negatively related to *the initial systemic importance* of banks. I thus do not find any effect for the largest and the most systemic banks. In both cases, these findings can be explained by the fact that large and systemic banks benefited from implicit state guarantees before deposit insurance adoption. Therefore, they already escaped market discipline and they do not take advantage from adoption of an explicit deposit insurance scheme. Second, I show that bank responsiveness is negatively related to their *initial leverage* leading to a convergence process among banks: those which are initially highly leveraged appear to be insensitive to deposit insurance adoption. This second features of deposit insurance adoption could be related to capital requirement : banks with a high initial leverage have much less room to increase it before capital constraint binds.

These results point out that deposit insurance adoption does not generate a build-up of fragility among a small set of banks, be they initially highly leveraged, relatively large or too-systemic-to-fail. However, they also indicate that the whole domestic banking industry tends to be less adequately capitalized after the implementation of deposit insurance.

6.3.1 The Mitigating Effects of Relative Size and Systemic Importance

There is no reason to consider that banks should react uniformly to the introduction of a deposit insurance scheme. The responses of banks depends entirely on the implicit subsidy they receive from deposit insurance adoption. This implicit subsidy is largely determined by the intensity of the market discipline existing before adoption: the stronger the market discipline ex ante, the larger the subsidy ex post. For instance, a bank that would not be subject to market discipline ex ante should not react at all to the deposit insurance adoption. If we thus assume that banks that are systemically important already benefit from implicit state guarantees, we should observe a negative relation between the responses of banks and their *systemic importance*. In this paragraph, I present evidence supporting this hypothesis.

For this purpose, I use two indicators of systemic importance: *the bank market share in terms of deposits*, *i.e* the domestic relative size, and *the ratio of bank assets to GDP*. However, these indicators of systemic importance are likely to be impacted by deposit insurance adoption. To address this endogeneity issue (Roberts and Whited (2011)), I use the pre-treatment value of these two measures. Say differently, I utilize indicators that are computed over the period preceding adoption. Formally, I define the two indicators of ex ante systemic importance as an average value over the period before adoption (excluding the year of adoption)[34]:

$$\overline{MarketShare_{i,j}} = \frac{\sum_{t<\hat{t}_j-1} MarketShare_{i,j,t}}{(\hat{t}_j - 1 - t_0)}$$

$$\overline{AssetOverGDP_{i,j}} = \frac{\sum_{t<\hat{t}_j-1} AssetOverGDP_{i,j,t}}{(\hat{t}_j - 1 - t_0)}$$

Implementation of this methodology leads to the loss of a large number of observations.[35] I then extend the baseline specification by including in-

[34]The results presented below are robust to alternative definitions of the ex ante indicators used. In unreported regressions, I confirm the results using indicators of systemic importance computed over the period that precedes adoption including the year of adoption, or excluding the year of adoption and the year immediately before. I have also used indicators computed as the last value one or two periods before adoption.

[35]This is so because all the countries having adopted a deposit insurance scheme before the 90's have no observations for these years. But most of these observations are not used to identify the effect of deposit insurance adoption in the baseline specification

teraction terms between these indicators and the deposit insurance adoption dummy:

$$Risk_{i,j,t} = \alpha + \beta \cdot DI_{j,t} + \omega \cdot DI_{j,t} \cdot \overline{MarketShare_{i,j}} + \mu \cdot \overline{MarketShare_{i,j}} \tag{6.6}$$
$$\theta_t \cdot \overline{MarketShare_{i,j}} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t}$$

$$Risk_{i,j,t} = \alpha + \beta \cdot DI_{j,t} + \omega \cdot DI_{j,t} \cdot \overline{AssetOverGDP_{i,j}} + \mu \cdot \overline{AssetOverGDP_{i,j}} \tag{6.7}$$
$$\theta_t \cdot \overline{AssetOverGDP_{i,j}} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t}$$

where u_i and θ_t are bank and year fixed-effects. The identification of ω relies of on the comparison *within the same country* of the response of banks with different systemic importance to deposit insurance adoption. We expect to find a negative coefficient for β and a positive coefficient for ω: as banks become more and more systemically important, the intensity of their response should diminish.

The set of interaction terms between time fixed-effects and ex ante indicators ($\theta_t \cdot \overline{MarketShare_{i,j}}$ and $\theta_t \cdot \overline{AssetOverGDP_{i,j}}$) aims to control for the fact that banks with different ex ante systemic importance may also have different evolutions of risk-taking over time within the same country (independently of the deposit insurance adoption). I do not want to confound the heterogeneity in the risk-shifting effect of deposit insurance depending on the ex ante systemic importance with "natural" differences in the evolution of risk-taking over time for banks having different ex ante systemic importance. The results are presented in tables 10 and 11. In the first two columns, I replicate the baseline specification to confirm that the previous findings remain valid after the loss of observations caused by the construction of systemic indicators. The next two columns present the results of specification (6.4) and (6.7) without any covariates while the last two columns include these latter.

The first two columns corroborate that introducing a deposit insurance scheme increases the leverage ratio of banks and then translates into higher risk of insolvency. Note that the loss of observations discussed just above induces only a very small change in the magnitude of $\hat{\beta}$ in both regressions : it confirms that most of these lost observations are without any effects on the estimation of $\hat{\beta}$. When considering the results of specification (6.4) and (6.7), it appears that deposit insurance adoption continues to have a negative and significant on the banks' capital buffer, *i.e* $\hat{\beta} < 0$. However, the coefficient associated with the interaction terms $DI_{j,t} \cdot \overline{MarketShare_{i,j}}$ and $DI_{j,t} \cdot \overline{AssetOverGDP_{i,j}}$ is positive and significantly different from zero indicating that the response of banks to the implementation of deposit insurance is strongly mitigated by systemic importance of the banks.

For instance, in the case of the Capital-to-Assets ratio, the effect of deposit insurance diminishes with systemic importance and becomes indistinguishable from zero for banks having an ex ante domestic market share larger than 23%, which corresponds to banks in the last decile of the distribution. Similarly, the effect of deposit insurance becomes insignificantly different from zero when banks have an ex ante ratio of assets over GDP larger than 24% : those banks belong to the top 5% of the distribution. All these results remain valid if I use alternative indicators like the market share in terms of assets or liabilities and the ratio of liabilities over GDP.

There is an important conclusion that can be drawn from these findings. First, the restricted set of banks that can be considered as systemically important, those who are commonly referred to as *too big to fail*, seems to be insensitive to adoption of deposit insurance. One plausible explanation is that these very large banks were perceived by depositors as benefiting from implicit state guarantees *before* deposit insurance adoption. Alternatively, we could think about systemic importance as a source of market power that makes the banks less sensitive to market discipline by depositors. In both cases, it strongly reduces the implicit subsidy they get from deposit insurance. Conversely, small banks are intensively monitored by depositors in absence of safety net : they are immediately punished for any diminution of their capital buffer. As a result, they take the greatest advantage from the relaxation of market discipline induced by deposit insurance adoption.

These results are consistent with previous findings of Ioannidou and Penas (2010) showing that differences between large and small banks in term of risky loans origination are reduced by deposit insurance. They are also in line with the paper of Gropp and Vesala (2004), but the strategy implemented in this paper has two advantages compared with their study. First, it controls for the possible endogenous reaction of systemic indicators to deposit insurance adoption as well as for the bias introduced by changes in coverage of BankScope. Second it does not use ad hoc threshold to define systemic banks. However, the present results could be perceived as inconsistent with those of Demirguc-Kunt and Huizinga (2012) who establish that systemically large banks are subject to greater market discipline because they appear to be *too big to save*.[36] But, both findings can be reconciled if we consider that deposit insurance is not a credible protection for those banks that are *too big to save*: they are thus not impacted by deposit insurance adoption as shown in this paper.

Finally, the findings presented in this section suggest that, by allowing small and non systemic banks to reduce their capital buffer, deposit insurance adoption is likely to promote competition on the banking market by reducing the comparative advantage of large and systemic financial institutions.[37] Interestingly, this effect has often been stated as an important motivation for adopting a system of deposit insurance (Garcia (2000) and Demirgüç-Kunt et al. (2008)).

6.3.2 Deposit Insurance Adoption and Leverage: a Convergence Process Across Banks

It is equally important to examine how the risk-shifting effect of deposit insurance is distributed across banks with heterogeneous initial capital buffer. From an aggregate perspective, understanding which banks react the most to deposit insurance adoption according to their initial leverage is essential. Indeed, financial stability is impacted differently depending on whether a small group of highly leveraged banks tends to become even more under-capitalized or whether safer banks start to catch up more risky ones. In the first case, we face a build-up of fragility in a small segment of the banking market. In the second case, the risk-shifting effect of deposit insurance adoption is spread across the entire banking system.

To investigate this question, I use the same methodology as before. I start by computing indicators of ex ante leverage by taking the average value before adoption of two proxies for leverage: the Capital-to-Assets ratio and the *Liabilities-to-Equity ratio*. Then, I interact these indicators with the deposit insurance dummy. Formally, I run the following regressions:

$$\begin{aligned} Risk_{i,j,t} &= \alpha + \beta \cdot DI_{j,t} + \omega \cdot DI_{j,t} \cdot \overline{CAR_{i,\,j}} + \mu \cdot \overline{CAR_{i,\,j}} \\ &\quad \theta_t \cdot \overline{CAR_{i,\,j}} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \end{aligned} \tag{6.8}$$

[36]Note that the authors document the opposite pattern when using the market share which is now consistent with the results established in this paper.

[37]Cordella and Yeyati (2002) or Matutes and Vives (1996) examine theoretically the relationships between deposit insurance and competition

$$\begin{aligned} Risk_{i,j,t} &= \alpha + \beta \cdot DI_{j,t} + \omega \cdot DI_{j,t} \cdot \overline{LiabToEquity_{i,\,j}} + \mu \cdot \overline{LiabToEquity_{i,\,j}} \\ & \theta_t \cdot \overline{LiabToEquity_{i,\,j}} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \epsilon_{i,j,t} \end{aligned} \tag{6.9}$$

The results can be found in the table 12 and 13 and they are unambiguous. We observe a negative impact of ex ante leverage ratio on the banks' response to deposit insurance adoption: the least leveraged banks before the reform are those reacting the most intensively to deposit insurance adoption. For instance, the coefficients in the third column of table 13 indicate that there is no effect of deposit insurance adoption on the Capital-to-Assets ratio for banks having an initial *Liabilities-to-Equity ratio* above 16: the 10% most leveraged banks are thus insensitive to introduction of deposit guarantees. Similarly, only banks having an initial Capital-to-Assets ratio above 12% reduce their capital buffer after deposit insurance adoption.

Following the implementation of deposit insurance, deposits financing becomes relatively cheaper compare to capital. Indeed, deposit insurance schemes induce important deviations from the Modigliani-Miller world (Admati et al. (2011)). Hence, in absence of actuarially fair premia (in particular risk-based premia), highly capitalized banks should substitute deposits to equity. Otherwise, they would implicitly subsidize most leveraged banks, because they would pay the same premium without taking full advantage from the cheaper source of funding provided by insured deposits. This explains why we observe an important response from the most capitalized banks. In contrast, the absence of reaction from least capitalized banks could also be explained by regulatory capital constraints : they have less room to reduce their Capital-to-Assets ratio by substituting deposits to equity financing. [38] Accordingly, deposit insurance adoption tends to make the distribution of leverage ratios across banks much more concentrated around its mean. The between standard deviation of the Capital-to-Assets ratio decreases from 0.13 before adoption to 0.10 after adoption. This pattern can also be observed by looking at figure 3.

All these findings established in this section are robust to the inclusion of country-specific trends, both linear and quadratic. More importantly, they are robust to the inclusion of banking crisis index and banking supervision

[38] However regulatory constraints cannot fully explain the relation exhibited because even in restricting the sample to banks having an initial Capital-to-Assets ratio higher than 15% or 20%, we continue to capture a negative relation between initial leverage and banks' reaction. Results available upon request.

index as well as interaction terms of these two indicators with the various measures used : market share, assets over GDP and initial leverage. In other words, I continue to capture the heterogeneous responses of banks to deposit insurance adoption even after controlling for the heterogeneous effects of banking crisis and banking supervision on banks according to their size, systemic importance and initial market share. In other words, this heterogeneity with respect to deposit insurance adoption cannot be confused with heterogeneity with respect to banking crisis or other changes in banking regulation. All these robustness checks are presented in tables 17, 18, 19 and 20.

Overall, we bring evidence that small, non systemic and well-capitalized banks react the most to deposit insurance adoption. There are two important lessons from this analysis. First, we observe a *convergence* across banks in terms of leverage ratio after the implementation of deposit insurance: initially well-capitalized banks increase much more their leverage after deposit insurance adoption than initially highly leveraged banks. Second, deposit insurance adoption has some important *competitive effects* by removing the comparative advantage of large and systemic banks and by improving competition on the banking market. But, if not supplemented with additional regulatory constraints, adopting a deposit insurance also makes the whole banking system less well-capitalized and thus less resilient to large shocks.

7 Robustness checks

In this section, I present additional robustness checks. I start by replicating the results using a sample restricted to countries adopting a deposit insurance scheme during the period under study. Second, I use the first-difference estimators to confirm the validity of the results under weaker assumptions. Third, I deal with a crucial issue in a quasi difference-in-difference framework: the so-called serial correlation issue. For the sake of brevity, I present the other robustness checks in the appendix B.

Treated sample As explain in the section concerning the data, I choose to perform the estimations on the largest sample, mainly to have a stable control group over time. This sample includes countries for which we do not observe implementation of deposit insurance scheme during the period covered.[39] It can be countries that adopted a deposit insurance scheme before the first year of the period studied (1986), or countries that do not have a deposit insurance system yet. When using this extended sample, the control group on which the identification relies includes these countries. A classical robustness check consists in replicating the regressions using a different control group (Roberts and Whited (2011)). In particular, finding different results would cast doubt on the fundamental common trend assumption. I thereby restrict the sample by excluding countries with no policy change. The results are shown in table 14.

For both the leverage ratio and the distance-to-default, the coefficient associated with the deposit insurance adoption dummy remains highly significant. The magnitude of the coefficients are only slightly lower than those from the baseline regressions. Hence, the main result established previously appears robust to the use of alternative control group.

First-Difference estimation The baseline specification (5.1) estimates the impact of deposit insurance adoption in a *fixed-effects* framework. However, the consistency of these estimates relies on strong assumptions. In this paragraph, I present the results of regressions using the *first-difference* estimators. Under the assumption of homoskedasticity and no serial correlation in the error term, the fixed-effects estimators is more efficient than the first-difference estimators. In contrast, consistency of the first-difference estimator is obtained under a weaker assumption: the first-difference of the idiosyncratic error must be serially uncorrelated, *i.e* error terms must follow a random walk (Wooldridge (2010)). In addition, this first-difference estimation helps to know whether the deposit insurance adoption has an *immediate impact* on leverage. Precisely, I regress the following specification:

$$\Delta Risk_{i,j,t} \quad = \quad \beta \cdot \Delta DI_{j,t} + \gamma \cdot \Delta X_{i,j,t} + \Delta\theta_t + \Delta\epsilon_{i,j,t}$$

where Δ is the difference operator. The results are presented in table 15.

Additionally, I also perform an estimation allowing for bank-specific trends.[40] This model writes:

[39] See table 1

[40] These class of models are called *correlated random trend models*. See Wooldridge (2010) p. 315 and also http://www.cemmap.ac.uk/resources/imbens_wooldridge/slides_11.pdf

$$Risk_{i,j,t} \quad = \quad \alpha + \beta \cdot DI_{j,t} + \gamma \cdot X_{i,j,t} + \theta_t + u_i + \phi \cdot Trend_t \cdot u_i + \epsilon_{i,j,t}$$

If we first-difference this model, we get:

$$\Delta Risk_{i,j,t} \quad = \quad \beta \cdot \Delta DI_{j,t} + \gamma \cdot \Delta X_{i,j,t} + \Delta\theta_t + u_i + \Delta\epsilon_{i,j,t}$$

Observe that we have now bank fixed-effects directly in the first-differenced equation. Hence, we can estimate this equation by using the fixed-effect estimator or by differencing again. The results being roughly the same I only present those from the fixed-effects regressions. These results are also reported in table 15.

The coefficient in table 15 largely confirms the previous results. First, the two risk indicators give additional evidence that adoption of deposit insurance favors high leverage ratios even under weaker statistical assumptions. Second, while the fixed-effects estimator assesses the long term effect of deposit insurance, the first-difference estimator captures the immediate jump in risk-taking. Here, we see that providing guarantees on deposits has an immediate effect on the bank capital buffer. This short term reaction of banks to deposit insurance adoption is somewhat lower in magnitude than their long term response. Third, allowing for bank-specific trends in leverage and risk of insolvency gives almost the same results as before. We continue to observe an effect that is statistically and economically significant. Overall these findings do not alter the main message of the paper.

Serial correlation In their influential paper, Bertrand et al. (2004) argue that estimations based on the difference-in-difference method are subject to a possibly severe serial correlation problems. To overcome this issue, they propose a range of solutions. The present paper implements the solution that proposes to ignore time-series information when computing standard errors. First, the risk-taking measurements are regressed on bank and year fixed-effects and possibly, on all the covariates previously used except the deposit insurance adoption dummy. The residuals of the treated countries only[41] are then divided into two groups: residuals from years before adoption, and those from years after adoption. Finally, the effect of adoption is estimated by OLS: the residuals are regressed on the deposit insurance dummy in a two periods model. The results are shown in table 16.

[41] i.e. those for which we observe an adoption during the period covered.

For each dependent variable, the first column uses the *combined residual* $(\epsilon_{i,j,t} + u_i)$ and the second column uses the *overall error component* alone $(\epsilon_{i,j,t})$. We are mainly interested by the statistical significance of the coefficients. Most the coefficient presented in this table are highly significant : only the coefficient in column 3 is not significant at all while the coefficient in the first column is significantly distinct from zero at the 10% level. In conclusion, the potential serial correlation issue threatening the difference-in-difference estimates of policy change does not appear to be a crucial problem in the present paper.

Further robustness checks In the appendix B, I run several additional robustness checks: I consider the potential problem posed by Mergers and Acquisitions, I replicates the baseline regression on various sub-samples, and I add bank-level control variables. Moreover, replications of the baseline specification using the z-score in level and various versions of the log of z-score can also be found in this appendix B. The main finding of this paper is always confirmed: banks tend to adopt more risky behavior after deposit insurance adoption, especially by reducing their capital buffer.

8 Conclusion

In this paper, I investigate the causal relation existing between adoption of deposit insurance and bank risk-taking by underlying the prominent role of changes in leverage. This is clearly a topical issue as the recent events in Cyprus has shown. The moral hazard related to guarantees offered to banks has been largely discussed when states and central banks have provided bailouts to the banking industry in the midst of the recent financial crisis. Focusing on the effect of deposit insurance adoption on bank capital buffer, this paper aims to provide a contribution to this very challenging issue.

This study shows that we observe a significant increase in bank risk of insolvency after introduction of deposit insurance. The magnitude of this effect is roughly 30% to 45% of one sample standard deviation of the various risk indicators used. Above all, this paper argues that the downward shift in bank distance-to-default is mainly caused by an increase in bank leverage: banks tend to reduce their capital buffer by almost 15% after implementation of deposit insurance. These results are consistent with both the theoretical and the empirical literature.

In order to rule out the possibility of spurious correlations due to reverse causation or simultaneity, I run various sensitivity checks. In particular, I run a falsification test showing that bank capital buffer starts to decrease significantly only after deposit insurance adoption and not before. Additionally, I perform a placebo analysis in simulating false deposit insurance adoption. I conclude that the observed effect cannot be explained by pre-existing upward shifts in bank risk-taking. Second, I also discuss the possibility that the adverse effect captured in this paper could be related to simultaneous changes in banking regulation or by contemporaneous banking crises. Tests provided in this paper show that it is quite unlikely.

Most importantly, I find that relatively large and systemic banks as well as most highly leveraged banks tend to be unresponsive to the deposit insurance adoption. I cannot capture any significant change in the leverage ratio for the top 10% most systemic banks or for the top 20% most leveraged banks. The first result is consistent with the view that systemic banks are not subject to market discipline because they benefit from implicit state guarantees. Hence, they do not react to the introduction of explicit deposit insurance. As such, deposit insurance could have important *competitive effects* by removing the comparative advantage of large and systemic banks. The second result is interesting because it sheds light on the *convergence process* induced by deposit insurance adoption. To avoid to subsidize highly leveraged banks, well-capitalized banks reduce significantly more their capital buffer. Overall, these results offer contrasting views on deposit insurance: only the less fragile banks seem to increase their leverage after deposit insurance adoption but the whole domestic banking industry is less adequately capitalized after implementation of deposit guarantees.

All the results presented in this paper tend to confirm that deposit insurance adoption induces an excessive risk-taking by banks, especially with regard to bank leverage. These findings are in line with the previous research concerning the relaxation of market discipline caused by deposit insurance adoption. Recently, in reaction to the financial crisis of 2008 many countries have decided to increase the amount of deposits covered by guarantee funds (USA and EU for instance). Other countries (Australia, New Zealand) have adopted an explicit deposit insurance scheme for the first time in their history. The European Union want to design a unified deposit insurance system in the very next years. The results established in this paper reaffirm the necessity to control adequately the perverse incentives that deposit insurance provides to banks with a particular focus on the capital buffer of banks. The decision to include a raw leverage ratio in the Basel III regulatory standards can be viewed as an important step in this direction. But results presented in this paper suggest that introduction of risk-based premia, in particular premia based on the capital buffer of banks (as proposed by Bond and Crocker (1993) and more recently by Acharya et al. (2010)) would help to mitigate the perverse incentives provided by deposit insurance.

Bibliography

Abiad, A., Detragiache, E., and Tressel, T. (2010). A new database of financial reforms. *IMF Staff Papers*, 57(2):281–302. 19, 21

Acharya, V., Mehran, H., Schuermann, T., and Thakor, A. (2011). Robust capital regulation. Technical report. 17

Acharya, V., Schnabl, P., and Richardson, M. (2012). How banks played the leverage game. *Restoring financial stability: how to repair a failed system*, pages 83–100. 2, 10

Acharya, V. V., Santos, J. A. C., and Yorulmazer, T. (2010). Systemic risk and deposit insurance premiums. *Economic Policy Review*, (Aug):89–99. 8, 35

Admati, A. R., DeMarzo, P. M., Hellwig, M. F., and Pfleiderer, P. C. (2011). Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is not Expensive. *SSRN eLibrary*. 17, 29

Adrian, T. and Shin, H. S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*, 19(3):418–437. 2

Allen, F. and Gale, D. (1998). Optimal financial crises. *Journal of Finance*, 53(4):1245–1284. 6

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33. 6

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 1 edition. 19, 20

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21(1):1–42. 21

Barth, J. R., Caprio Jr, G., and Levine, R. (2001). The regulation and supervision of banks around the world - a new database. Policy Research Working Paper Series 2588, The World Bank. 65

Beck, T. (2008). Resolution of failed banks by deposit insurers: Cross-country evidence. Technical report. 3, 10

Beck, T., De Jonghe, O., and Schepens, G. (2011). Bank competition and stability: Cross-country heterogeneity. Technical report. 10

Berger, A. N., Herring, R. J., and Szego, G. P. (1995). The role of capital in financial institutions. *Journal of Banking & Finance*, 19(3-4):393–430. 17

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275. 16, 32

Bertrand, M. and Mullainathan, S. (2003). Enjoying the quiet life? corporate governance and managerial preferences. *Journal of Political Economy*, 111(5):1043–1075. 21

Bond, E. W. and Crocker, K. J. (1993). Bank capitalization, deposit insurance, and risk categorization. *The Journal of Risk and Insurance*, 60(4):pp. 547–569. 2, 35

Boyd, J. H. and De Nicolò, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, 60(3):1329–1343. 15

Boyd, J. H. and Runkle, D. E. (1993). Size and performance of banking firms : Testing the predictions of theory. *Journal of Monetary Economics*, 31(1):47–67. 11

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, 23(1):77–100. 2

Calomiris, C. W. and White, E. N. (1994). The origins of federal deposit insurance. In *The Regulated Economy: A Historical Approach to Political Economy*, NBER Chapters, pages 145–188. National Bureau of Economic Research, Inc. 4, 24

Cordella, T. and Yeyati, E. L. (2002). Financial opening, deposit insurance, and risk in a model of banking competition. *European Economic Review*, 46(3):471–485. 28

DeLong, G. and Saunders, A. (2011). Did the introduction of fixed-rate federal deposit insurance increase long-term bank risk-taking? *Journal of Financial Stability*, 7(1):19–25. 3

Demirguc-Kunt, A. and Detragiache, E. (2002). Does deposit insurance increase banking system stability? an empirical investigation. *Journal of Monetary Economics*, 49(7):1373–1406. 3, 21

Demirguc-Kunt, A. and Huizinga, H. (2004). Market discipline and deposit insurance. *Journal of Monetary Economics*, 51(2):375–399. 2, 3, 7, 17

Demirgüç-Kunt, A. and Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics*, 98(3):626–650. 10

Demirguc-Kunt, A. and Huizinga, H. (2012). Do we need big banks? evidence on performance, strategy and market discipline. Working Paper 8276, BIS. 27

Demirguc-Kunt, A. and Kane, E. J. (2002). Deposit insurance around the globe: Where does it work? *Journal of Economic Perspectives*, 16(2):175–195. 4, 24

Demirgüç-Kunt, A., Kane, E. J., and Laeven, L., editors (2008). *Deposit Insurance around the World: Issues of Design and Implementation*, volume 1 of *MIT Press Books*. The MIT Press. 4, 5, 21, 24, 28, 65

Demirguc-Kunt, A., Karacaovali, B., and Laeven, L. (2005). Deposit insurance around the world : a comprehensive database. Policy Research Working Paper Series 3628, The World Bank. 65, 66

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–19. 2, 6

Diamond, D. W. and Rajan, R. G. (2005). Liquidity shortages and banking crises. *Journal of Finance*, 60(2):615–647. 6

Duprey, T. and Lé, M. (2012). Bankscope dataset: getting started. Version 1. 67, 68

Garcia, G. (2000). Deposit insurance: Actual and good practices. IMF Occasional Papers 197, International Monetary Fund. 28

Gropp, R. and Heider, F. (2010). The determinants of bank capital structure. *Review of Finance*, 14(4):587–622. 14, 17, 71

Gropp, R. and Vesala, J. (2004). Deposit insurance, moral hazard, and market monitoring. *Review of Finance*, 8(4):571–602. 17, 27

Gruber, J. and Hungerman, D. M. (2008). The church versus the mall: What happens when religion faces increased secular competition? *The Quarterly Journal of Economics*, 123(2):831–862. 20

Ioannidou, V. P. and Penas, M. F. (2010). Deposit insurance and bank risk-taking: Evidence from internal loan ratings. *Journal of Financial Intermediation*, 19(1):95–115. 3, 7, 27

Kalemli-Ozcan, S., Sorensen, B., and Yesiltas, S. (2011). Leverage across firms, banks, and countries. NBER Working Papers 17354, National Bureau of Economic Research, Inc. 14

Kane, E. (1989). *The S & L Insurance Mess: How Did it Happen?* Urban Institute Press. 3

Karas, A., Pyle, W., and Schoors, K. (2013). Deposit insurance, banking crises, and market discipline: Evidence from a natural experiment on deposit flows and rates. *Journal of Money, Credit and Banking*, 45(1):179–200. 2

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review*, 80(5):1183–1200. 2, 7, 17

Kennedy, P. E. (1981). Estimation with correctly interpreted dummy variables in semilogarithmic equations [the interpretation of dummy variables in semilogarithmic equations]. *American Economic Review*, 71(4):801. 16

Laeven, L. (2002). International evidence on the value of deposit insurance. *The Quarterly Review of Economics and Finance*, 42(4):721–732. 3

Laeven, L. and Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93(2):259–275. 10

Lemmon, M. L., Roberts, M. R., and Zender, J. F. (2008). Back to the beginning: Persistence and the cross-section of corporate capital structure. *Journal of Finance*, 63(4):1575–1608. 14

Lepetit, L. and Strobel, F. (2011). Bank insolvency risk and time-varying z-score measures. *Working Paper*. 70

Marcus, A. J. and Shaked, I. (1984). The valuation of fdic deposit insurance using option-pricing estimates. *Journal of Money, Credit and Banking*, 16(4):446–60. 2, 4

Martínez-Peria, M. S. and Schmukler, S. (2002). Do depositors punish banks for bad behavior? market discipline, deposit insurance, and banking crises. In Hernández, L., Schmidt-Hebbel, K., Editor), N. L. S., and (S, K. S.-H., editors, *Banking, Financial Integration, and International Crises*, volume 3 of *Central Banking, Analysis, and Economic Policies Book Series*, chapter 5, pages 143–174. Central Bank of Chile. 2, 3

Matutes, C. and Vives, X. (1996). Competition for deposits, fragility, and insurance. *Journal of Financial Intermediation*, 5(2):184–216. 28

Merton, R. C. (1977). An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory. *Journal of Banking & Finance*, 1(1):3–11. 2, 7

Nicolò, G. D., Boyd, J. H., and Jalal, A. M. (2007). Bank risk-taking and competition revisited: New theory and new evidence. IMF Working Papers 06/297, International Monetary Fund. 70

Nier, E. and Baumann, U. (2006). Market discipline, disclosure and moral hazard in banking. *Journal of Financial Intermediation*, 15(3):332–361. 17

Pennacchi, G. (2006). Deposit insurance, bank regulation, and financial system risks. *Journal of Monetary Economics*, 53(1):1–30. 2

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1):435–480. 16

Roberts, M. R. and Whited, T. M. (2011). Endogeneity in Empirical Corporate Finance. *Social Science Research Network Working Paper Series*. 14, 20, 25, 31

Saunders, A. and Wilson, B. (1999). The impact of consolidation and safety-net support on canadian, us and uk banks: 1893-1992. *Journal of Banking & Finance*, 23(2-4):537–571. 17

Valencia, F. and Laeven, L. (2008). Systemic banking crises: A new database. IMF Working Papers 08/224, International Monetary Fund. 19, 21

Wheelock, D. C. (1992). Deposit insurance and bank failures: New evidence from the 1920s. *Economic Inquiry*, 30(3):530–43. 3

Wheelock, D. C. and Wilson, P. W. (1995). Explaining bank failures: Deposit insurance, regulation, and efficiency. *The Review of Economics and Statistics*, 77(4):689–700. 3

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*, volume 1 of *MIT Press Books*. The MIT Press. 31

9 Tables and Figures

Figure 1

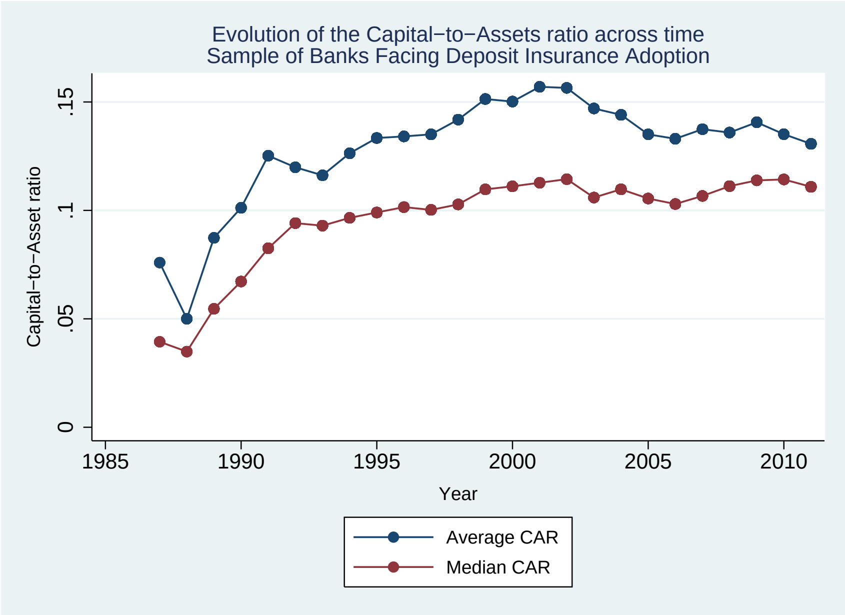
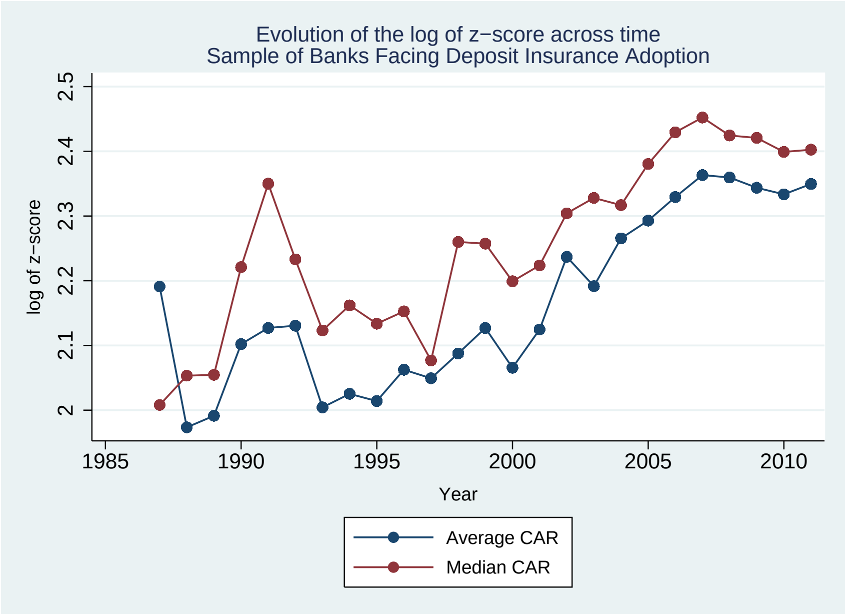


Figure 2



Note: These figures show the evolutions of the average and the median Capital-to-Assets ratio (top) and log of z-score (bottom) across time computed over the sample of banks that face a deposit insurance adoption.

Figure 3

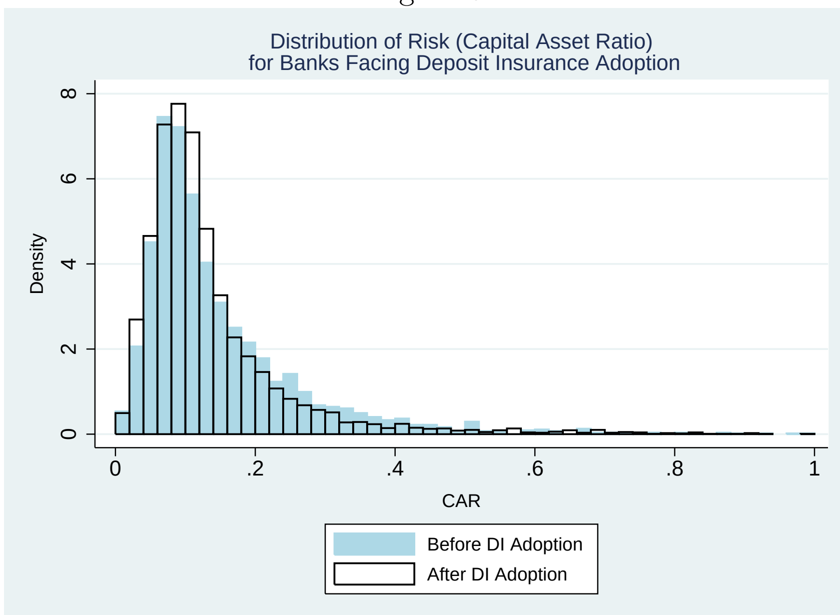
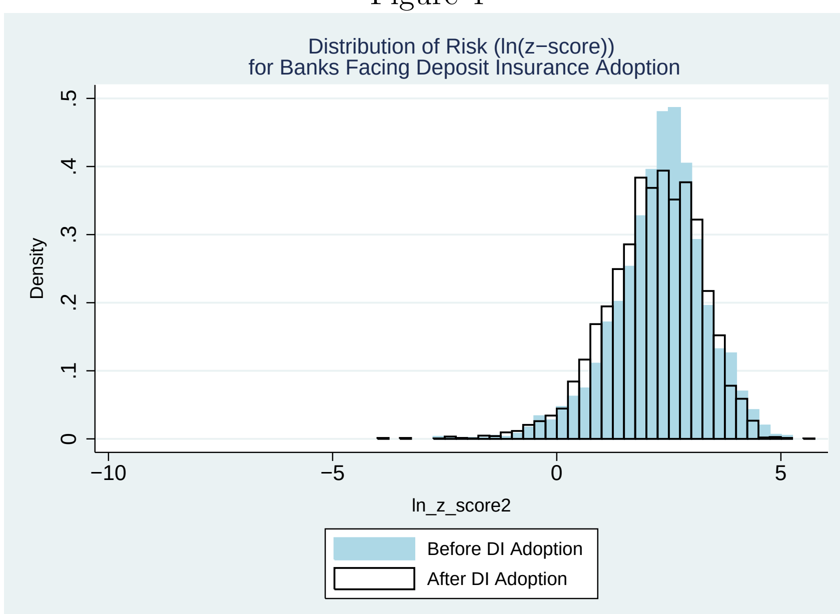


Figure 4



Note: These figures show the distribution of the average Capital-to-Assets ratio (top) and log of z-score (bottom) *before* (in blue) and *after* (in white) deposit insurance adoption. The sample of banks is restricted to banks for which we have observations before and after deposit insurance adoption. A lower value signals an increase in leverage (top) or in the probability of default (bottom).

Figure 5

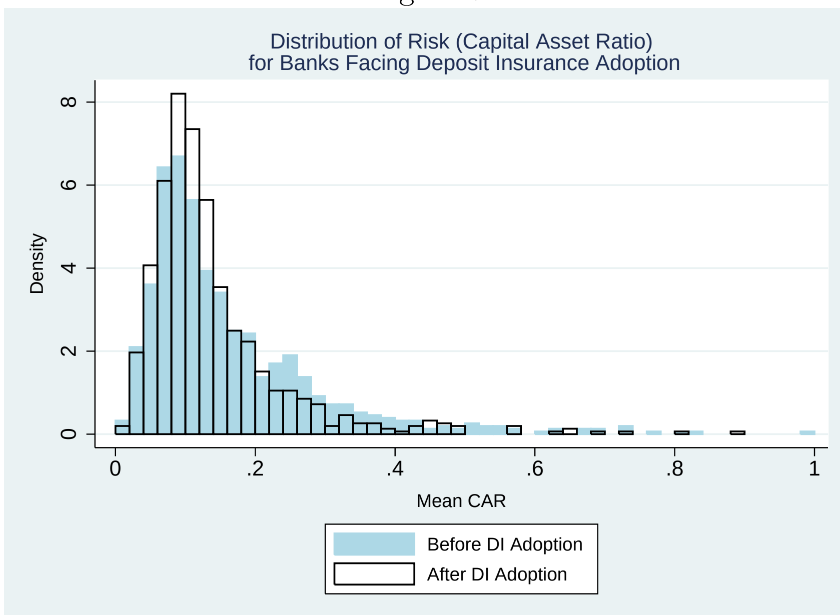
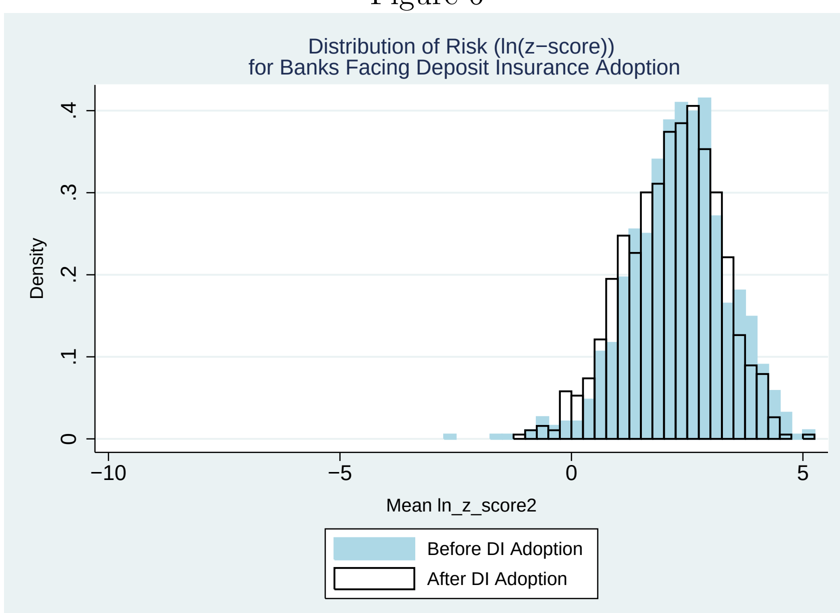


Figure 6



Note: These figures show the distribution of the average Capital-to-Assets ratio (top) and log of z-score (bottom) *before* (in blue) and *after* (in white) deposit insurance adoption. The sample of banks is restricted to banks for which we have observations before and after deposit insurance adoption. There is only one observation per banks and per period (before/after). A lower value signals an increase in the leverage (top) or in the probability of default (bottom).

Figure 7

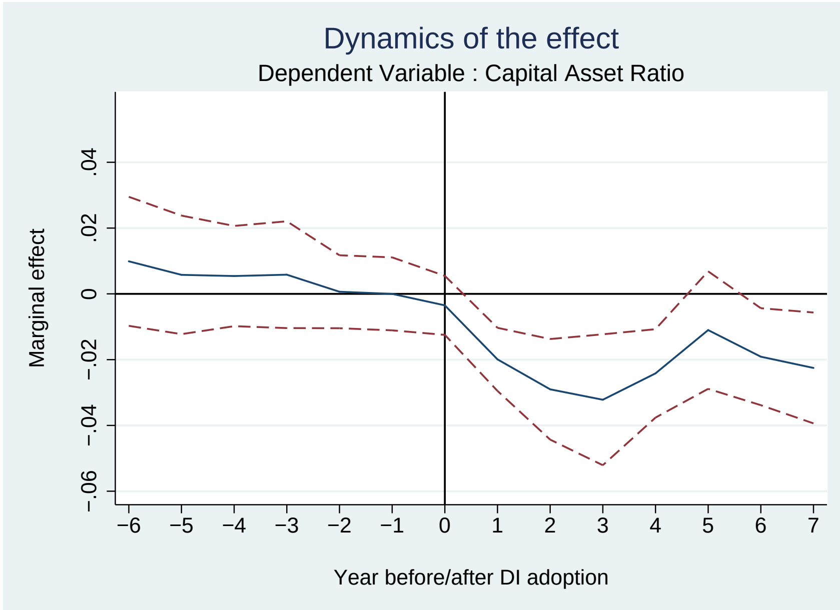
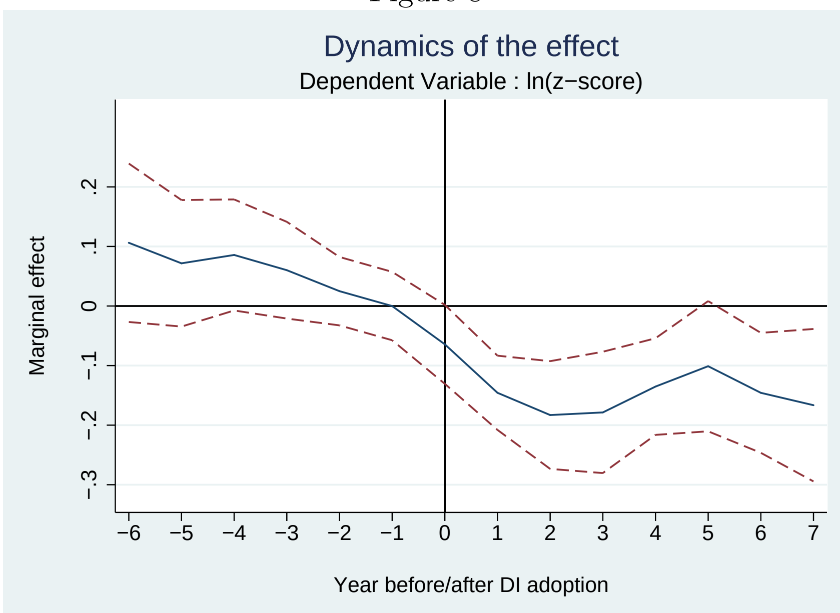


Figure 8



Note: These figures show the dynamics of the impact of deposit insurance adoption on the Capital-to-Assets ratio (top) and the log of z-score (bottom).The solid blue line represents the point estimate while the dashed red lines display 95% confidence intervals. The underlying regression used a set of dummy variables for each year before and after deposit insurance adoption. The two very last dummy variables take the value of 1 for all the periods more than 6 years before adoption and for all the periods more than 7 year after the adoption. The reference year is the year preceding adoption (year -1).

Table 1: Deposit Insurance Scheme. Year of Adoption

Country Name	Year of Adoption	Nb of banks	Country Name	Year of Adoption	Nb of banks
USA	1934	9935	LITHUANIA	1996	11
INDIA	1961	80	SUDAN	1996	17
NORWAY	1961	122	SWEDEN	1996	101
DOMINICAN REP.	1962	48	MACEDONIA	1997	14
PHILIPPINES	1963	36	SLOVAKIA	1997	18
GERMANY	1966	2215	THAILAND	1997	25
CANADA	1967	46	ALGERIA	1998	15
FINLAND	1969	11	CROATIA	1998	42
JAPAN	1971	681	ESTONIA	1998	6
BELGIUM	1975	78	INDONESIA	1998	99
NETHERLANDS	1979	43	LATVIA	1998	22
FRANCE	1980	399	BULGARIA	1999	23
SPAIN	1980	175	ECUADOR	1999	22
UNITED KINGDOM	1982	193	BAHAMAS	2000	21
TURKEY	1983	32	BELARUS	2000	11
BANGLADESH	1984	30	EL SALVADOR	2000	16
SWITZERLAND	1984	405	KAZAKHSTAN	2000	17
COLOMBIA	1985	34	VIETNAM	2000	29
KENYA	1986	37	CYPRUS	2001	17
TRINIDAD & TOB.	1986	10	HONDURAS	2001	22
DENMARK	1987	104	JORDAN	2001	12
ITALY	1987	692	NICARAGUA	2001	6
SRI LANKA	1987	11	SLOVENIA	2001	22
AUSTRIA	1988	270	ALBANIA	2002	9
NIGERIA	1988	37	BOLIVIA	2002	14
IRELAND	1989	27	BOSNIA-HERZ.	2002	16
LUXEMBOURG	1989	126	GUATEMALA	2002	36
SERBIA	1989	31	UKRAINE	2002	46
MEXICO	1990	43	MALTA	2003	7
PERU	1991	25	URUGUAY	2003	30
HUNGARY	1993	32	MOLDOVA REP.	2004	15
MOROCCO	1993	11	PARAGUAY	2004	22
BAHRAIN	1994	21	RUSSIAN FED.	2004	875
TANZANIA	1994	22	ARMENIA	2005	14
UGANDA	1994	11	MALAYSIA	2006	46
ARGENTINA	1995	71	SINGAPORE	2006	15
CZECH REP.	1995	26	AZERBAIJAN	2007	18
GREECE	1995	25	HONG KONG	2007	28
OMAN	1995	8	AUSTRALIA	2008	19
POLAND	1995	44	YEMEN	2008	11
PORTUGAL	1995	29	NEW ZEALAND	2009	13
BRAZIL	1996	150	CAMEROON	2011	7
KOREA REP. OF	1996	16	GABON	2011	4

The following countries don't have explicit deposit insurance scheme: Angola, Benin, Botswana, Burkina Faso, Burundi, Cambodia, China People's Rep., Costa Rica, Egypt, Georgia Rep. Of, Ghana, Iran, Israel, Ivory Coast, Kuwait, Macau, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Pakistan, Panama, Qatar, Saudi Arabia, Senegal, South Africa, Syria, Tunisia and Zambia

Table 2: Summary statistics

Variable	N	Mean	SD	P25	Median	P75
	Main Sample					
ln(z-score)	205583	3.12	1.03	2.48	3.23	3.84
z-score	206534	35.85	41.12	11.76	25.09	46.21
Capital-to-Assets ratio	207060	0.11	0.09	0.07	0.09	0.12
Return on Average Assets	206536	0.01	0.03	0.00	0.01	0.01
Log of Total Assets	207060	6.29	2.66	4.52	5.61	7.28
Net Interest Revenue / Avg Assets	205549	0.03	0.02	0.03	0.03	0.04
Deposit Market Share	207060	0.01	0.05	0.00	0.00	0.00
Liquid Assets/Total Assets	207060	0.16	0.16	0.05	0.10	0.20
Cost-to-Income ratio	204539	0.71	0.39	0.58	0.67	0.77
HHI index on Deposits	2319	0.29	0.24	0.13	0.22	0.35
GDP growth (annual %)	2319	0.04	0.04	0.02	0.04	0.06
Inflation (annual %)	2319	19.63	154.11	2.23	4.58	9.38
Log of GDP per capita	2319	10.62	2.13	9.40	10.35	11.91
	Sample Limited to Banks Facing Deposit Insurance Adoption					
ln(z-score)	24963	2.55	1.05	1.94	2.65	3.27
z-score	25191	20.36	23.44	6.77	14.04	26.17
Capital-to-Assets ratio	25329	0.15	0.13	0.07	0.11	0.18
Return on Average Assets	25192	0.01	0.04	0.00	0.01	0.02
Log of Total Assets	25329	8.01	2.85	6.11	7.50	9.25
Net Interest Revenue / Avg Assets	24932	0.05	0.06	0.02	0.04	0.06
Deposit Market Share	25329	0.04	0.10	0.00	0.00	0.02
Liquid Assets/Total Assets	25329	0.31	0.21	0.15	0.26	0.42
Cost-to-Income ratio	24648	0.70	0.39	0.52	0.67	0.84
HHI index on Deposits	1072	0.29	0.23	0.13	0.22	0.35
GDP growth (annual %)	1072	0.04	0.05	0.02	0.04	0.06
Inflation (annual %)	1072	28.32	186.84	2.39	4.66	9.58
Log of GDP per capita	1072	10.40	2.31	8.97	9.96	11.45

Table 3: Descriptive Statistics Before and After Adoption

Variable	N	Mean	SD	P25	Median	P75
	Before Deposit Insurance Adoption					
log of z-score	2625	2.29	1.02	1.73	2.38	2.93
Capital-to-Assets ratio	2699	0.1493	0.1193	0.0747	0.1113	0.1849
Liabilities-to-Equity ratio	2697	10.24	13.96	4.41	7.97	12.37
	After Deposit Insurance Adoption					
log of z-score	5836	2.16	1.05	1.52	2.24	2.90
Capital-to-Assets ratio	5956	0.1352	0.1098	0.0734	0.1049	0.1567
Liabilities-to-Equity ratio	5952	10.93	16.24	5.37	8.53	12.62

This table provides descriptive statistics before and after deposit insurance adoption for banks facing an adoption. *N* is the number of observation. *Mean* is the mean value. *SD* is the standard deviation of banks. *p25*, *Median* and *p75* are the 25th, the 50th and the 75th percentile threshold.

Table 4: Baseline specification

	Capital-to-Assets Ratio	ln(z-score)	Capital-to-Assets Ratio	ln(z-score)
Deposit Insurance	-0.0230**	-0.1797**	-0.0189**	-0.1924**
	(0.0030)	(0.0001)	(0.0071)	(0.0000)
HHI index on deposit			0.0047	-0.0889
			(0.7059)	(0.3782)
GDP growth (annual %)			-0.0150	0.4881
			(0.8086)	(0.3042)
Inflation (annual %)			-0.0000	0.0001
			(0.9085)	(0.3455)
Log of GDP per capita			-0.0333*	0.1110
			(0.0354)	(0.3558)
Observations	207,060	205,583	207,060	205,583
Number of id	18,825	18,814	18,825	18,814
Adjusted R-squared	0.0056	0.0183	0.0067	0.0195
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not include the contribution of bank fixed effects to the explained variance.

Table 5: Sample Standard Deviation of Risk-Taking

		Mean	Std. Dev.	Observations
Capital-to-Assets ratio	overall	.1504638	.1342641	N = 25329
	between		.1214999	n = 2686
	within		.0723533	T-bar = 9.43001
log of z-score	overall	2.551565	1.045221	N = 24963
	between		.9901594	n = 2682
	within		.4017789	T-bar = 9.30761

This table provides additional descriptive statistics for banks facing an adoption. *N* is the number of observation. *Mean* is the mean value. *Within Std. Dev.* is the standard deviation of within banks, *i.e.* the deviation from each individual's average. *Between Std. Dev.* is the standard deviation across banks, *i.e* the standard deviation of individual's average. *p25*, *Median* and *p75* are the 25th, the 50th and the 75th percentile threshold.

Table 6: Specification with linear country-specific trends

	Capital-to-Assets Ratio	ln(z-score)	Capital-to-Assets Ratio	ln(z-score)
Deposit Insurance	-0.0204**	-0.1541**	-0.0204**	-0.1465**
	(0.0087)	(0.0000)	(0.0021)	(0.0000)
HHI index on deposit			0.0108	0.0453
			(0.3590)	(0.5645)
GDP growth (annual %)			-0.0733	-0.3077
			(0.1357)	(0.3078)
Inflation (annual %)			-0.0000	0.0000
			(0.7891)	(0.6070)
Log of GDP per capita			-0.0365	0.3453
			(0.2444)	(0.0580)
Observations	207,060	205,583	207,060	205,583
Number of id	18,825	18,814	18,825	18,814
Adjusted R-squared	0.0213	0.0528	0.0223	0.0534
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country
Ctry Specific Trend	Linear	Linear	Linear	Linear

** $p<0.01$, * $p<0.05$. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 7: Specification with linear and quadratic country-specific trends

	Capital-to-Assets Ratio	ln(z-score)	Capital-to-Assets Ratio	ln(z-score)
Deposit Insurance	-0.0179*	-0.1330**	-0.0176**	-0.1295**
	(0.0128)	(0.0000)	(0.0085)	(0.0000)
HHI index on deposit			0.0077	0.0334
			(0.5123)	(0.6466)
GDP growth (annual %)			-0.0466	-0.2418
			(0.3579)	(0.4136)
Inflation (annual %)			0.0000	0.0001**
			(0.1369)	(0.0021)
Log of GDP per capita			-0.0767*	0.0773
			(0.0394)	(0.6660)
Observations	207,060	205,583	207,060	205,583
Number of id	18,825	18,814	18,825	18,814
Adjusted R-squared	0.0261	0.0620	0.0273	0.0623
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country
Ctry Specific Trend	Lin.& Quad.	Lin.& Quad.	Lin.& Quad.	Lin.& Quad.

** $p<0.01$, * $p<0.05$. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 8: Falsification test

	Capital-to-Assets Ratio	ln(z-score)	Capital-to-Assets Ratio	ln(z-score)
Years ≤ -6	0.0099	0.1062		
	(0.3197)	(0.1164)		
Year -6			0.0014	-0.0140
			(0.8369)	(0.7468)
Years -5	0.0058	0.0717	-0.0036	-0.0396
	(0.5263)	(0.1836)	(0.5802)	(0.4823)
Year -4	0.0054	0.0858	-0.0040	-0.0256
	(0.4827)	(0.0710)	(0.6567)	(0.6622)
Year -3	0.0058	0.0602	-0.0036	-0.0512
	(0.4784)	(0.1447)	(0.7331)	(0.3641)
Year -2	0.0006	0.0250	-0.0087	-0.0865
	(0.9090)	(0.3906)	(0.3624)	(0.2035)
Year -1			-0.0094	-0.1115
			(0.3829)	(0.1432)
Year of adoption	-0.0035	-0.0642	-0.0319*	-0.2780*
	(0.4430)	(0.0573)	(0.0222)	(0.0119)
Year 1	-0.0199**	-0.1457**	-0.0129	-0.1757*
	(0.0001)	(0.0000)	(0.2522)	(0.0140)
Year 2	-0.0290**	-0.1830**	-0.0293*	-0.2572**
	(0.0003)	(0.0001)	(0.0199)	(0.0022)
Year 3	-0.0322**	-0.1786**	-0.0384**	-0.2945**
	(0.0017)	(0.0007)	(0.0083)	(0.0038)
Year 4	-0.0242**	-0.1352**	-0.0416*	-0.2901**
	(0.0005)	(0.0013)	(0.0109)	(0.0066)
Year 5	-0.0110	-0.1010	-0.0336*	-0.2468**
	(0.2245)	(0.0697)	(0.0118)	(0.0054)
Year 6	-0.0191*	-0.1457**	-0.0204	-0.2126*
	(0.0116)	(0.0049)	(0.1152)	(0.0169)
Years ≥ 7	-0.0225**	-0.1665*	-0.0285*	-0.2572**
	(0.0093)	(0.0112)	(0.0291)	(0.0079)
Observations	207,060	205,583	207,060	205,583
Number of id	18,825	18,814	18,825	18,814
Adjusted R-squared	0.0076	0.0194	0.0076	0.0194
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. In this table, the variables *Year "i"* or *Year "-i"* are dummy variables taking the value of one exactly "i" years before or after deposit insurance adoption. The variables *Years ≥ "i"* or *Years ≤ "-i"* are dummy variable taking the value of one "i" years, "i+1" years, "i+2" years... after deposit insurance adoption or "-i" years, "-i-1" years, "-i-2" years... before deposit insurance adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 9: Controlling for Banking Crises and Simultaneous Changes in Banking Regulation

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0189**	-0.1924**	-0.0187**	-0.1912**	-0.0192*	-0.1939**	- 0.0183*	-0.1891**	-0.0190*	-0.1929**
	(0.0071)	(0.0000)	(0.0080)	(0.0000)	(0.0195)	(0.0002)	(0.0251)	(0.0002)	(0.0209)	(0.0002)
HHI index on deposit	0.0047	-0.0889	0.0043	-0.0908	-0.0011	-0.1002	-0.0019	-0.1067	-0.0012	-0.1010
	(0.7059)	(0.3782)	(0.7286)	(0.3636)	(0.9426)	(0.3872)	(0.8985)	(0.3497)	(0.9352)	(0.3823)
GDP growth (annual %)	-0.0150	0.4881	-0.0054	0.5330	-0.0241	0.6068	-0.0232	0.6062	-0.0164	0.6547
	(0.8086)	(0.3042)	(0.9328)	(0.3174)	(0.7415)	(0.2970)	(0.7459)	(0.2830)	(0.8301)	(0.3125)
Inflation (annual %)	-0.0000	0.0001	-0.0000	0.0001	-0.0000	0.0001	-0.0000	0.0001	-0.0000	0.0001
	(0.9085)	(0.3455)	(0.8699)	(0.3645)	(0.9536)	(0.3564)	(0.7307)	(0.4659)	(0.9301)	(0.3713)
Log of GDP per capita	-0.0333*	0.1110	-0.0312*	0.1208	-0.0334	0.1010	-0.0281	0.1481	-0.0320	0.1092
	(0.0354)	(0.3558)	(0.0481)	(0.3028)	(0.0566)	(0.4301)	(0.1155)	(0.2885)	(0.0677)	(0.3921)
Banking Crisis			0.0023	0.0109					0.0016	0.0101
			(0.2615)	(0.6811)					(0.4579)	(0.7171)
Banking Supervision					-0.0026	-0.0331			-0.0025	-0.0326
					(0.4258)	(0.2233)			(0.4347)	(0.2181)
Financial Reform Index							-0.0024*	-0.0227*		
							(0.0316)	(0.0165)		
Observations	207,060	205,583	207,060	205,583	200,354	199,075	200,354	199,075	200,354	199,075
Number of id	18,825	18,814	18,825	18,814	18,184	18,174	18,184	18,174	18,184	18,174
Adjusted R-squared	0.0067	0.0195	0.0068	0.0196	0.0071	0.0213	0.0074	0.0218	0.0071	0.0214
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. In this table, the variable *Banking Crisis* is a country-year-specific dummy taking the value of one during the years a given country experiences a banking crisis. The variable *Banking Supervision* is a country-year-specific index taking values between 0 and 3 in which higher values indicate more banking regulation. The variable *Financial Reform Index* is a country-year-specific index taking values between 0 and 21 in which higher values indicate higher financial liberalization. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 10: The Effect of Systemic Importance: ex ante Market Share in terms of Deposits

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0226**	-0.1725**	-0.0276**	-0.1975**	-0.0234**	-0.1744**
	(0.0009)	(0.0000)	(0.0003)	(0.0000)	(0.0004)	(0.0001)
DI* ex ante Market Share			0.0708**	0.4127*	0.0758**	0.4230*
			(0.0089)	(0.0440)	(0.0092)	(0.0453)
HHI index on deposit					0.0334*	0.1783
					(0.0329)	(0.1390)
GDP growth (annual %)					0.0751*	0.6731**
					(0.0397)	(0.0044)
Inflation (annual %)					-0.0000	0.0000
					(0.7681)	(0.5674)
Log of GDP per capita					-0.1239**	-0.4932**
					(0.0000)	(0.0077)
Observations	9,610	9,394	9,610	9,394	9,610	9,394
Number of id	891	889	891	889	891	889
Adjusted R-squared	0.0167	0.0166	0.0212	0.0272	0.0494	0.0397
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full
Year*ex ante Market Share	NO	NO	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In this table, the variable *DI*ex ante Market Share* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the systemic importance of each bank before adoption. It is computed as the average value of the market share on deposits over the periods preceding adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 11: The Effect of Systemic Importance: ex ante Total Assets over GDP

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0226**	-0.1725**	-0.0251**	-0.1894**	-0.0202**	-0.1638**
	(0.0009)	(0.0000)	(0.0003)	(0.0000)	(0.0008)	(0.0000)
DI*ex ante Assets/GDP			0.0584**	0.3355**	0.0491**	0.2914**
			(0.0010)	(0.0053)	(0.0010)	(0.0090)
HHI index on deposit					0.0241	0.0899
					(0.1578)	(0.4984)
GDP growth (annual %)					0.0831*	0.7133**
					(0.0239)	(0.0024)
Inflation (annual %)					-0.0000	0.0001
					(0.9604)	(0.3827)
Log of GDP per capita					-0.1228**	-0.4762**
					(0.0000)	(0.0087)
Observations	9,610	9,394	9,610	9,394	9,610	9,394
Number of id	891	889	891	889	891	889
Adjusted R-squared	0.0167	0.0166	0.0193	0.0267	0.0453	0.0374
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full
Year*ex ante Assets/GDP	NO	NO	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In this table, the variable *DI*ex ante Assets over GDP* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the systemic importance of each bank before adoption. It is computed as the average value of the ratio of Assets to GDP over the periods preceding adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 12: The Effect of the Initial Capital-to-Assets Ratio

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0226**	-0.1725**	0.0210**	-0.0657	0.0188*	-0.0680
	(0.0009)	(0.0000)	(0.0050)	(0.1943)	(0.0196)	(0.1812)
DI*ex ante CAR			-0.2570**	-0.5907*	-0.2270**	-0.4829
			(0.0001)	(0.0150)	(0.0005)	(0.0522)
HHI index on deposit					0.0141	0.0472
					(0.2851)	(0.6517)
GDP growth (annual %)					0.0662*	0.6618**
					(0.0458)	(0.0046)
Inflation (annual %)					-0.0000*	0.0000
					(0.0459)	(0.8278)
Log of GDP per capita					-0.0751**	-0.2538
					(0.0050)	(0.1315)
Observations	9,610	9,394	9,610	9,394	9,610	9,394
Number of id	891	889	891	889	891	889
Adjusted R-squared	0.0167	0.0166	0.1811	0.1080	0.1914	0.1119
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full
Year*ex ante CAR	NO	NO	YES	YES	YES	YES

** p<0.01, * p<0.05. In this table, the variable *DI*ex ante CAR* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the leverage of each bank before adoption. It is computed as the average value of the Capital-to-Assets ratio over the periods preceding adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 13: The Effect of the Initial Liabilities-to-Equity ratio

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0204**	-0.1410**	-0.0363**	-0.2630**	-0.0313**	-0.2403**
	(0.0030)	(0.0001)	(0.0001)	(0.0000)	(0.0002)	(0.0000)
DI*ex ante Liab.-to-Equity			0.0018**	0.0139**	0.0016**	0.0132**
			(0.0008)	(0.0000)	(0.0010)	(0.0000)
HHI index on deposit					0.0333*	0.1135
					(0.0277)	(0.2444)
GDP growth (annual %)					0.0676	0.5711**
					(0.0720)	(0.0046)
Inflation (annual %)					-0.0000	0.0000
					(0.5287)	(0.7548)
Log of GDP per capita					-0.1010**	-0.3627*
					(0.0002)	(0.0262)
Observations	8,116	7,940	8,116	7,940	8,116	7,940
Number of id	755	753	755	753	755	753
Adjusted R-squared	0.0166	0.0195	0.0465	0.0868	0.0703	0.0947
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full
Year*ex ante Liab.-to-Equity	NO	NO	YES	YES	YES	YES

** p<0.01, * p<0.05. In this table, the variable *DI*ex ante Liab.-to-Equity* is an interaction term between the deposit insurance adoption dummy and indicator reflecting the leverage of each bank before adoption. It is computed as the average value of the the Liabilities-to-Equity ratio over the periods preceding adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 14: Sample of Treated Countries

	Capital-to-Assets ratio	ln(z-score)	Capital-to-Assets ratio	ln(z-score)
Deposit Insurance	-0.0204**	-0.1506**	-0.0135*	-0.1204**
	(0.0077)	(0.0004)	(0.0263)	(0.0016)
HHI index on deposit			0.0160	0.0379
			(0.3969)	(0.7982)
GDP growth (annual %)			0.0030	0.3732
			(0.9353)	(0.1685)
Inflation (annual %)			-0.0000	0.0001
			(0.9551)	(0.2911)
Log of GDP per capita			-0.1220**	-0.4341**
			(0.0000)	(0.0013)
Observations	25,329	24,963	25,329	24,963
Adjusted R-squared	0.0099	0.0114	0.0235	0.0170
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country
Number of id	2,686	2,682	2,686	2,682

** $p<0.01$, * $p<0.05$. In this table, the sample excludes all countries with no change in the Deposit Insurance dummy, *i.e.* those having already adopted a Deposit Insurance scheme before the first year of the sample and those without Deposit Insurance Scheme at the end of the sample. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 15: First-Difference and Bank-specific Trends

	First Difference				Bank Specific Trend			
	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
ΔDeposit Insurance	-0.0103**	-0.1052**	-0.0111**	-0.1130**	-0.0088**	- 0.0908**	-0.0096**	-0.0955**
	(0.0019)	(0.0006)	(0.0010)	(0.0002)	(0.0088)	(0.0065)	(0.0033)	(0.0026)
ΔHHI index on deposit			0.0090	0.0134			0.0079	-0.0048
			(0.2732)	(0.7899)			(0.2882)	(0.9266)
ΔGDP growth (annual %)			-0.0601	-0.2662			-0.0626	-0.3871
			(0.2622)	(0.3226)			(0.2649)	(0.1746)
ΔInflation (annual %)			-0.0000	0.0000*			-0.0000	0.0000
			(0.0576)	(0.0480)			(0.0794)	(0.0914)
ΔLog of GDP per capita			-0.0135	0.3133**			-0.0184	0.4508**
			(0.5116)	(0.0043)			(0.5378)	(0.0046)
Observations	186,899	185,042	186,899	185,042	186,899	185,042	186,899	185,042
Number of id					18,825	18,812	18,825	18,812
Adjusted R-squared	0.0025	0.0090	0.0032	0.0093	0.0046	0.0082	0.0056	0.0086
Regression Type	Bank FD	Bank FD	Bank FD	Bank FD	Bank FD	Bank FD	Bank FD	Bank FD
FE	NO	NO	NO	NO	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. The first four columns presents the First-Difference estimator while the next four columns present the random correlated trend model allowing for unit-specific (here bank) trends. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 16: Aggregating across Country and Ignoring Time Series Information

	Residuals Including Bank Fixed-effect				Residuals Excluding Bank Fixed-effect			
	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0158	-0.1745**	-0.0137	-0.1675**	-0.0177**	-0.1373**	-0.0133*	-0.1344**
	(0.0643)	(0.0078)	(0.1885)	(0.0071)	(0.0059)	(0.0000)	(0.0165)	(0.0002)
Observations	8,674	8,480	8,674	8,480	8,674	8,480	8,674	8,480
Adjusted R-squared	0.0041	0.0059	0.0018	0.0055	0.0130	0.0190	0.0074	0.0182
Regression Type	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
FE	NO	NO	NO	NO	NO	NO	NO	NO
Year FE	NO	NO	NO	NO	NO	NO	NO	NO
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Treated	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
First-Stage Year FE	YES	YES	YES	YES	YES	YES	YES	YES
First-Stage Controls	NO	NO	YES	YES	NO	NO	YES	YES

** $p<0.01$, * $p<0.05$. Here I implement the method suggested by Bertrand and Duflo (2004) to deal with serial correlation. First, I regress the various risk proxies on banks FE, year FE and possibly covariates, excluding the deposit insurance dummy . Then I divide the residuals of banks treated, i.e. those occuring an adoption of deposit insurance in the period covered, into to groups: residuals from years before the adoptions and residuals from years after the adoptions. Finally, I regress these residuals on the deposit insurance dummy in a two-peridos panel frameworks. The first four columns present regression from the the combined residual (including the banks FE) while the last four columns present regressions from the the overall error component alone. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 17: The Effect of Systemic Importance: ex ante Market Share in terms of Deposits. Robustness Checks

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0235**	-0.1626**	-0.0210**	-0.1527**	-0.0210**	-0.1486**	- 0.0224**	-0.1671**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)
DI*ex ante Market Share	0.0548**	0.3597**	0.0545*	0.2682	0.0543*	0.2663	0.0672*	0.2540
	(0.0039)	(0.0063)	(0.0428)	(0.1684)	(0.0406)	(0.1770)	(0.0230)	(0.2731)
HHI index on deposit			0.0159	0.1516	0.0155	0.1676	0.0195	0.1584
			(0.3756)	(0.0920)	(0.3949)	(0.0681)	(0.3550)	(0.1445)
GDP growth (annual %)			0.0749**	0.4454**	0.0781**	0.3728*	0.0785**	0.4153**
			(0.0060)	(0.0044)	(0.0083)	(0.0339)	(0.0037)	(0.0071)
Inflation (annual %)			0.0000	0.0001	0.0000	0.0001	0.0000	0.0001*
			(0.2036)	(0.0757)	(0.2300)	(0.0859)	(0.1241)	(0.0489)
Log of GDP per capita			-0.1053**	-0.0288	-0.1028**	-0.0825	-0.1284**	-0.1191
			(0.0018)	(0.9153)	(0.0011)	(0.7467)	(0.0003)	(0.6867)
Banking Crisis (BC)					0.0004	-0.0402		
					(0.9468)	(0.3803)		
BC*ex ante Market Share					0.0214	-0.0514		
					(0.4387)	(0.8818)		
Banking Supervision (BS)							-0.0107	-0.0633
							(0.0510)	(0.0884)
BS*ex ante Market Share							0.0330	0.3159*
							(0.1760)	(0.0407)
Observations	9,610	9,394	9,610	9,394	9,610	9,394	7,808	7,632
R-squared			0.1399	0.1401	0.1400	0.1405	0.1227	0.1308
Number of id	891	889	891	889	891	889	739	737
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full	Full	Full
Year* ex ante Market Share	YES	YES	YES	YES	YES	YES	YES	YES
Ctry Specific Trend	YES	YES	YES	YES	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In this table, the variable *DI*ex ante Market Share* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the systemic importance of each bank before adoption. It is computed as the average value of the market share on deposits over the periods preceding adoption. The variable *BC*ex ante Market Share* is an interaction term between the Banking Crisis dummy and the indicator reflecting the systemic importance of each bank before adoption. The variable *BS*ex ante Market Share* is an interaction term between the Banking Supervision index and the indicator reflecting the systemic importance of each bank before adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 18: The Effect of Systemic Importance: ex ante Assets over GDP. Robustness Checks

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0216**	-0.1549**	-0.0188**	-0.1497**	-0.0189**	-0.1446**	- 0.0198**	-0.1652**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
DI*ex ante Assets/GDP	0.0383*	0.3072**	0.0307**	0.2982*	0.0295**	0.2950*	0.0312*	0.2746
	(0.0137)	(0.0025)	(0.0054)	(0.0195)	(0.0066)	(0.0189)	(0.0393)	(0.0764)
HHI index on deposit			0.0115	0.1055	0.0105	0.1249	0.0138	0.0939
			(0.5462)	(0.2703)	(0.5962)	(0.2054)	(0.5439)	(0.4169)
GDP growth (annual %)			0.0832**	0.4915**	0.0856**	0.4088*	0.0893**	0.4523**
			(0.0014)	(0.0009)	(0.0023)	(0.0126)	(0.0005)	(0.0023)
Inflation (annual %)			0.0000	0.0001*	0.0000	0.0001*	0.0000	0.0001
			(0.1027)	(0.0244)	(0.1416)	(0.0379)	(0.1742)	(0.0545)
Log of GDP per capita			-0.1088**	-0.0447	-0.1077**	-0.1071	-0.1317**	-0.1216
			(0.0011)	(0.8643)	(0.0006)	(0.6675)	(0.0002)	(0.6655)
Banking Crisis (BC)					0.0003	-0.0500		
					(0.9558)	(0.2597)		
BC*ex ante Assets/GDP					0.0303	0.0249		
					(0.3172)	(0.9630)		
Banking Supervision (BS)							-0.0098*	-0.0538
							(0.0398)	(0.1010)
BS*ex ante Assets/GDP							0.0623*	0.5257*
							(0.0362)	(0.0255)
Observations	9,610	9,394	9,610	9,394	9,610	9,394	7,808	7,632
R-squared			0.1348	0.1343	0.1349	0.1349	0.1193	0.1288
Number of id	891	889	891	889	891	889	739	737
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full	Full	Full
Year*ex ante Assets/GDP	YES	YES	YES	YES	YES	YES	YES	YES
Ctry Specific Trend	YES	YES	YES	YES	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In this table, the variable *DI*ex ante Assets over GDP* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the systemic importance of each bank before adoption. It is computed as the average value of the ratio of Assets to GDP over the periods preceding adoption. The variable *BC*ex ante Assets over GDP* is an interaction term between the Banking Crisis dummy and the indicator reflecting the systemic importance of each bank before adoption. The variable *BS*ex ante Assets over GDP* is an interaction term between the Banking Supervision index and the indicator reflecting the systemic importance of each bank before adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 19: The Effect of the Initial Capital-to-Assets Ratio. Robustness Checks

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	0.0357**	-0.0130	0.0216*	-0.0333	0.0206*	-0.0220	0.0295**	-0.0256
	(0.0000)	(0.6604)	(0.0140)	(0.5092)	(0.0163)	(0.6664)	(0.0038)	(0.6563)
DI*ex ante CAR	-0.3362**	-0.7936**	-0.2382**	-0.6470**	-0.2316**	-0.6828**	- 0.3070**	-0.8497**
	(0.0000)	(0.0000)	(0.0003)	(0.0059)	(0.0002)	(0.0057)	(0.0001)	(0.0008)
HHI index on deposit			0.0144	0.1082	0.0148	0.1291	0.0220	0.1238
			(0.3715)	(0.2292)	(0.3681)	(0.1567)	(0.2186)	(0.2186)
GDP growth (annual %)			0.0706*	0.4630**	0.0715*	0.3691*	0.0699*	0.4071**
			(0.0166)	(0.0022)	(0.0260)	(0.0329)	(0.0292)	(0.0083)
Inflation (annual %)			0.0000	0.0001*	0.0000	0.0001*	0.0000	0.0001*
			(0.1457)	(0.0137)	(0.1334)	(0.0136)	(0.1698)	(0.0209)
Log of GDP per capita			-0.0727*	0.0924	-0.0745*	0.0330	-0.0810*	0.0415
			(0.0228)	(0.7162)	(0.0103)	(0.8936)	(0.0182)	(0.8822)
Banking Crisis (BC)					0.0045	-0.0774		
					(0.4676)	(0.2138)		
BC*ex ante CAR					-0.0308	0.1511		
					(0.5468)	(0.5181)		
Banking Supervision (BS)							-0.0012	0.0021
							(0.8860)	(0.9721)
BS*ex ante CAR							-0.0439	-0.2555
							(0.4488)	(0.3416)
Observations	9,610	9,394	9,610	9,394	9,610	9,394	7,808	7,632
R-squared			0.2575	0.1837	0.2578	0.1844	0.2492	0.1743
Number of id	891	889	891	889	891	889	739	737
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full	Full	Full
Year*ex ante CAR	YES	YES	YES	YES	YES	YES	YES	YES
Ctry Specific Trend	YES	YES	YES	YES	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In this table, the variable *DI*ex ante CAR* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the leverage of each bank before adoption. It is computed as the average value of the Capital-to-Assets ratio over the periods preceding adoption. The variable *BC*ex ante CAR* is an interaction term between the Banking Crisis dummy and the indicator reflecting the leverage of each bank before adoption. The variable *BS*ex ante CAR* is an interaction term between the Banking Supervision index and the indicator reflecting the leverage of each bank before adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 20: The Effect of the Initial Liabilities-to-Equity ratio. Robustness Checks

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0319**	-0.2808**	-0.0333**	-0.2777**	-0.0337**	-0.2767**	-0.0380**	-0.3169**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DI*ex ante Liab.-to-Equity	0.0013**	0.0157**	0.0016**	0.0156**	0.0016**	0.0155**	0.0019**	0.0164**
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0007)	(0.0000)	(0.0008)	(0.0000)
HHI index on deposit			0.0106	0.0782	0.0093	0.0830	0.0205	0.1239
			(0.6221)	(0.4200)	(0.6547)	(0.3863)	(0.3744)	(0.2455)
GDP growth (annual %)			0.0832**	0.4763**	0.0914**	0.4631*	0.0855**	0.3668*
			(0.0036)	(0.0047)	(0.0020)	(0.0103)	(0.0028)	(0.0324)
Inflation (annual %)			0.0000*	0.0001**	0.0000*	0.0001**	0.0000*	0.0001**
			(0.0201)	(0.0046)	(0.0179)	(0.0053)	(0.0104)	(0.0043)
Log of GDP per capita			-0.0903**	-0.0468	-0.0823**	-0.0534	-0.1097**	-0.1178
			(0.0050)	(0.8293)	(0.0068)	(0.8030)	(0.0016)	(0.6317)
Banking Crisis (BC)					0.0089	0.0022		
					(0.2228)	(0.9602)		
BC*ex ante Liab.-to-Equity					-0.0004	-0.0011		
					(0.3830)	(0.6502)		
Banking Supervision (BS)							-0.0065	-0.0374
							(0.2611)	(0.4021)
BS*ex ante Liab.-to-Equity							-0.0000	0.0020
							(0.9033)	(0.4236)
Observations	8,116	7,940	8,116	7,940	8,116	7,940	6,678	6,538
R-squared			0.1712	0.1870	0.1719	0.1871	0.1522	0.1728
Number of id	755	753	755	753	755	753	633	631
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Sample	Full	Full	Full	Full	Full	Full	Full	Full
Year*ex ante Liab.-to-Equity	YES	YES	YES	YES	YES	YES	YES	YES
Ctry Specific Trend	YES	YES	YES	YES	YES	YES	YES	YES

** p<0.01, * p<0.05. In this table, the variable *DI*ex ante Liab.-to-Equity* is an interaction term between the deposit insurance adoption dummy and an indicator reflecting the leverage of each bank before adoption. It is computed as the average value of the the Liabilities-to-Equity ratio over the periods preceding adoption. The variable *BC*ex ante Liab.-to-Equity* is an interaction term between the Banking Crisis dummy and the indicator reflecting the leverage of each bank before adoption. The variable *BS*ex ante Liab.-to-Equity* is an interaction term between the Banking Supervision index and the indicator reflecting the leverage of each bank before adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

10 Online Appendix [For online publication only]

Appendix A

Deposit Insurance Scheme Database

There already exists two important databases about deposit insurance schemes. The first one is the "*Deposit Insurance Around the World data set*" constructed by Demirgüç-Kunt, Karacaovali and Laeven in 2003 (Demirguc-Kunt et al. (2005) and then Demirgüç-Kunt et al. (2008)). It lists numerous characteristics about deposit insurance schemes implemented around the world until 2003. It provides data like the year of introduction, the amount of deposits covered, the existence of coinsurance and many other features. The second one is the "*Bank Regulation and Supervision Database*" constructed by Barth, Caprio and Levine in 2001 (Barth et al. (2001)) and updated in 2008 and 2012.[42] It contains roughly the same kind of information than the previous ones (excepting the year of adoption however).

Unfortunately these two databases do not contain any information about recent, i.e. post-2003, deposit insurance adoptions. Above all, they sometimes provide different and contradicting information. As a first step, I compare these two databases to the data provided by reports from both the *International Association of Deposit Insurers* and the *The European Forum of Deposit Insurers* to build a unique and homogeneous database about deposit insurance scheme around the world. Especially, I use the four wave of the "*International Deposit Insurance Survey Questionnaire*" (2003, 2008, 2010 and 2011)[43] and the "*Deposit Guarantee Systems: EFDI's First Report*" (2006).[44] I also look at some reports of the Financial Sector Assessment Program[45] from the World Bank and the International Monetary Fund: in many cases, they provide information about the existence and the year of adoption of deposit insurance scheme. For European countries, I also confront the

[42] However the part concerning deposit insurance scheme doesn't seem to have been updated.

[43] http://www.iadi.org/Research.aspx?id=58

[44] http://www.efdi.net/documents.asp?Id=5&Cat=Efdi%20Publications

[45] http://lnweb90.worldbank.org/FPS/fsapcountrydb.nsf/

sources with a report from the European Commission.[46] Regarding countries from the MENA region, I used a document summarizing the main information about deposit insurance systems in this region.[47] Finally, the consistency of the year of adoption has also been inspected using the deposit insurance websites.[48]

The main task consist in checking the exact year of introduction of deposit insurance scheme. I also collect additional information about some deposit insurance features like the existence of coinsurance mechanism (yes/no), the nature of the premia collected (flat or risk-based), or the timing of the funding (ex ante, ex post, or both). However, there are important difficulties to get consistent, reliable and time-varying information about these features. In particular the various sources used do not indicate the year of implementation of these features. For instance, imagine a country that adopted a deposit insurance scheme in 1995. In the 2008 IADI survey, it is not possible to know whether this country have coinsurance mechanism since 1995 or whether such a feature have been implemented latter. Hence, these information can only be exploited cross-sectionally. Using these information in a time-varying framework would be at cost of strong assumptions.

In general, the previous sources provide a year of adoption corresponding to the date at which the parliament votes the law establishing the deposit insurance fund. It is very likely to observe some delay before the deposit insurance scheme becomes effective. When available, I take advantage from the month of adoption: when the date provides a month after July, I change the year of adoption by the year immediately following. At the end, I obtain a database describing the year of adoption and some features of deposit insurance schemes in 197 countries as shown in table 3.

Compared to the database of Demirguc-Kunt et al. (2005), I collect the year of adoption for 24 additional countries. For 34 countries, the date of adoption differs from the one of Demirguc-Kunt et al. (2005). For 19 of these 34 countries, the difference is related to the delay between enactment by the parliament and effective implementation as explained before. In these cases, the date of implementation is just one year after the one previously established. It remains 13 countries for which dates of adoption differ by more

[46] http://ec.europa.eu/internal_market/bank/guarantee/index_en.htm

[47] http://siteresources.worldbank.org/INTMNAREGTOPPOVRED/Resources/MENAFlagshipDeposits2_25_11.pdf

[48] http://www.cdic.ca/CDIC/Cooperation/IntlLinks/Pages/default.aspx or http://www.iadi.org/aboutIADI.aspx?id=48

than one year (*Argentina, Austria, Belarus, Bosnia-herzegovina, Bulgaria, Guatemala, Honduras, Malaysia, Mexico, Montenegro, Portugal, Spain, and Ukraine*). However, in most of the cases, these differences are related to longer delay between enactment and implementation.

Treatment of date

Most of the financial companies publish their account statements at the end of the year, namely in December. Nonetheless, sometimes banks use non-calendar fiscal years to report their balance sheet statement (in March for several big Japanese banks, in October for several big Canadian banks...). On the top of that, even though BankScope provides us only with annual data, for a few hundred observations you have duplicated observations for balance sheet statements that closed at several dates within a single year. So one needs to handle both the allocation issue over year t or $t-1$ as well as the duplicated issue of yearly financial statements published several times a year.

These differences raise an important issue. It is likely that one prefer to compare data of financial statements reported in March of year t with data of financial statements reported in December of year $t-1$ rather than with data of financial statements reported in December of year t. The help file from Duprey and Lé (2012) proposes a small program that handles the situation in a compact way. Here I summarize their method.

- First, I drop mid-year financial reports because it is uncertain to which year t or $t-1$ one should attribute the observation. Precisely, I drop observations with a month comprised between April and September.
- Then, I identify banks which have "natural" duplicates, i.e. banks with the same *id* having at least two observations within the same fiscal year. Essentially I remove an observation of the 30^{th} November 2012 if I have an observation for the 31^{th} December 2012. Precisely, I always keep the observation with:
  - the month closest to December and if necessary,
  - the day closest to the last day of the month.
- Third, if I have banks which report their financial account in March 2012, it makes more sense to consider it as end of 2011 data. So for

each observations with a reporting month before April, I replace the actual year, saying t, by the previous year, saying $t-1$.

- Last, note that the previous step is likely to create new duplicates. So once again, the best strategy would be to keep the observation that have the least forward looking information. Consequently, between two observations reporting the same year after the previous change, I keep the one with the variable *year* unchanged. For instance assume that I have two observations reported in 2011 after the previous step. Then I drop the observation reporting 2011 as year, with March as month (and so 2012 as "true" year), provided I have already an observation reporting 2011 as year, with September as month (and so 2011 as "true" year).

For more details, see Duprey and Lé (2012).

Restrictions imposed on the balance sheet data

First, I only work with *Commercial Banks*, *Savings Banks*, *Cooperative Banks*, *Real Estate & Mortgage Bank*, *Islamic Banks* and *Other Non Banking Credit Institution*: these are the financial institutions which are concerned by such an insurance scheme.[49] Second, BankScope indicates whether the data come from consolidated (coded as *C1* and *C2*) or unconsolidated accounts (coded as *U1* and *U2*). When a bank reports both consolidated and unconsolidated accounts in the sample, I keep only the unconsolidated entries to avoid double counting. The rationale for this choice is based on the observation that deposit insurance is generally provided by the host country to the subsidiaries operating in this country.

Furthermore, I exclude from the sample: banks that report less than five observations, and countries with less than fifty observations. Last, I also deal with the presence of several observations for a specific bank during a given fiscal year and the fact that some observations are reported *during* the fiscal year and not *at the end* of the fiscal year. The exact procedure implemented is described in the appendix A and additional information about BankScope can be found in Duprey and Lé (2012).

[49] The literature generally uses only the three first types of banks, but after looking in detail at the list of banks participating to the deposit insurance scheme in some countries, I note that the three last types of bank are very often members of the deposit insurance funds.

Appendix B

In this appendix, I present the additional robustness checks that have not been include in the paper for the sake of brevity

Placebo analysis

To complement the falsification test presented previously, I perform a placebo analysis to exclude any possibility of capturing pre-existing upward shift in risk-taking rather than the effect of deposit insurance adoption. The idea is to simulate "false" deposit insurance adoption before the true one. If these placebo laws exhibit positive and significant coefficients, it would raise doubts about the causality of the effect observed in the baseline specification. This complement the falsification test conducted before.

For this purpose I restrict the sample to the years preceding the true adoption and for each country I simulate deposit insurance adoption for each year before the true adoption. Recall that $\hat{t}_j$ is defined as the year in which a (true) deposit insurance has been implemented in country j. Our placebo dummy variables are defined as follow :

$$DI_{j,t}^{Placebo\,year\,k} = \begin{cases} 1 & if\, t \geqq \hat{t}_j - k \\ 0 & if\, t < \hat{t}_j - k \end{cases} for\, 3 \leq k \leq$$

Note there is no placebo dummy variables for the two year immediately preceding adoption, because we need at least two periods after adoption for a correct identification. Results concerning these placebo laws can be found in table 21. I only report results for the Capital-to-Assets ratio but results are similar for the log of z-score. As expected, none of these placebo laws are significantly different from zero except the last one but in this case the coefficients have the wrong sign: leverage appears to be decreasing. Above all, compared with the true deposit insurance dummy, the magnitude of these effects is much smaller (from 30% to 90% lower than the true effect). That is to say, we cannot capture any significant change in bank leverage during the period preceding deposit insurance adoption. This sensitivity test entirely confirm that reverse causality is unlikely to be an important issue.

Various *log of z-score*'s

Note that when using the z-score in a time-varying framework, there is an important issue to discuss: the way to compute the mean and the standard deviation of $ROAA_t$. There is no clear consensus about this issue. Lepetit and Strobel (2011) compares the various time-varying z-score used in the literature. They conclude that, while appealing the use of time-varying standard deviation of $ROAA_t$ is not the best way to compute the z-score. They also suggest to use the mean of $ROAA_t$ computed over the full period of analysis. However, they remark that contemporaneous value of $ROAA_t$ provides almost the same results. Here I use the contemporaneous value of $ROAA_t$ and a standard deviation of $ROAA_t$ computed over the full sample.

To confirm that the results are not affected by the way I choose to construct the z-score, I provide results using alternative z-score. In table 22, I present results for the log of z-score in which the Capital-to-Assets Ratio and the Return on Average Asset are computed using a moving average with two lags and two leads. I also report results for regression using a log of z-score in which the standard deviation of the *Return on Average Asset* is computed as the absolute deviation from the average returns (Nicolò et al. (2007) and Lepetit and Strobel (2011)) :

$$\sigma(ROAA_{i,t}) = \mid ROAA_{i,t} - \frac{\sum_t ROAA_{i,t}}{T} \mid$$

In addition, to confirm that the main conclusions are not related to the log transformation, I re-run various regressions implemented in this paper using the z-score itself. The results can be found in table 23.

The z-score replication confirms entirely the previously established results. However note that the magnitude of the coefficient is dramatically reduced when including country-specific trends. Concerning the coefficients from the regressions using alternative log of z-score, they are all highly significant and their magnitude is virtually similar. The main conclusions supported by this paper are thus independent from the way the z-score is computed.

Different samples

To make sure that the results established previously are not driven by some unobserved features of the main sample, I also run regressions using three distinct sub-samples.[50]

First, a sub-sample restricted to the *publicly listed banks* is derived from the original sample. Generally, listed banks provide more reliable balance-sheet data. They also form a relatively more homogeneous group of banks across countries what should improve quality of estimations. Finally, we could also conjecture that these banks are more monitored and hence market discipline is likely to be more effective for these banks. But focusing on these banks sensibly reduces the number of observations.

The second sub-sample addresses the issue of failed banks. A lot of papers has emphasized that BankScope may be subject to a survivorship bias, namely the fact that the Bureau van Dijk deletes historical information on banks that no longer exist in the latest release of this database (Gropp and Heider (2010)). However, the BankScope version used in this paper seems to be free from this survivorship bias.[51] While many researchers desire to be sure that their results are not affected by this survivorship bias, I face here the opposite issue: I want to make sure that the increase in risk-taking that I capture is not driven by some very risky banks that eventually went bankrupt. To address this issue, I restrict the sample to active banks in 2007, i.e. banks reporting information in 2007.[52] Consequently, all the banks that went bankrupt before this date are not include in the sample.

The third sub-sample just considers the possibility that the results are strongly driven by the end of the sample including the 2007-2009 financial crisis. Hence, I drop the years after 2007.

The results are shown in tables 24 and 25. The adverse effect of introducing a deposit insurance system is largely confirmed when using these three samples. The increase in risk-taking after adopting depositors protection fund remains statistically and economically significant in both sub-samples. The magnitude of the effect of deposit insurance is roughly unchanged. It is even slightly more pronounced in the case of listed banks. This observation is not surprising. We have supposed that these banks are more likely to face market discipline. Thus, they benefit more from relaxation of market

[50] For all these distinct samples the same restrictions as before are applied.

[51] For instance, AmTrade International Bank of Georgia failed in 2002 and the FDIC was unable to arrange a transfer of its deposits to another financial institution (http://www.fdic.gov/bank/individual/failed/amtrade.html). However, the balance sheets (up to 2002) of this bank are reported in BankScope and appears in the main sample.

[52] I choose the year 2007 to avoid the 2007-2009 financial crisis

discipline induced by deposit insurance.

Finally, note that I replicate the baseline regression after having dropped each countries from the main sample one after one. This aims to confirm that the results are not driven by a single country. In these 116 regressions, the main finding is always confirmed.[53]

Mergers and Acquisitions

The study of banking industry must deal with an important issue: the mergers and acquisitions. Mergers and acquisitions may induce large artificial changes in balance sheets provided by BankScope. Especially, large variations in the Capital-to-Assets ratio are likely to be observed after M&A. With respect to the question studied in this paper, M&A may bias the previous results if these artificial changes in the Capital-to-Assets ratio are correlated in some way with deposit insurance adoption. I tackle this issue by removing from the sample banks having a growth of asset by more than 50%. These results are displayed in table 26.

It appears that controlling explicitly for a potential bias due to M&A leaves the main findings totally unchanged.

Additional control variables

Finally, I replicate the baseline regressions (with and without linear or quadratic country-specific trends) and I include additional control variables at the bank-level. As explained before, including these variables may induce strong endogeneity issue, notably because these variables are likely to be affected by deposit insurance adoption. Even after including the bank-specific covariates, the risk-shifting effect of deposit insurance adoption remains, as it can be seen in table 27.

[53] Results available upon request

Tables and Figures

Figure 1

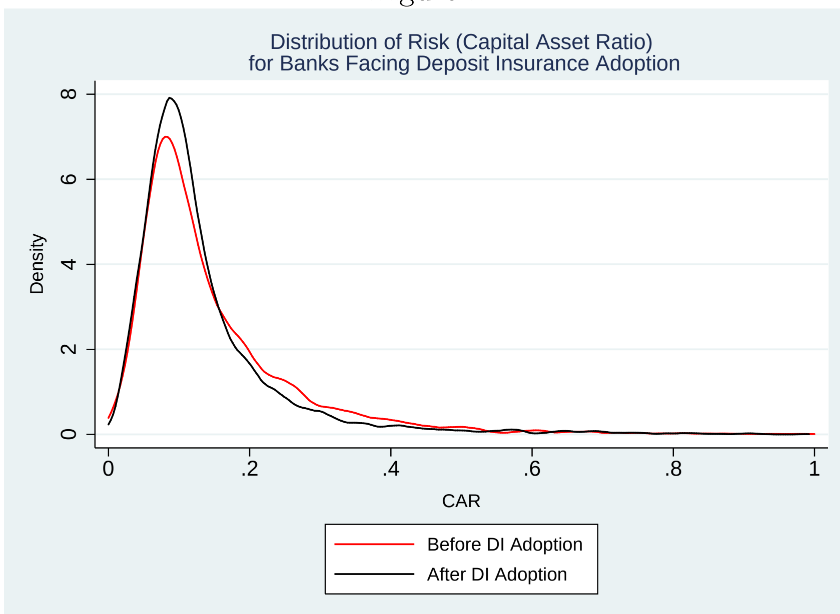
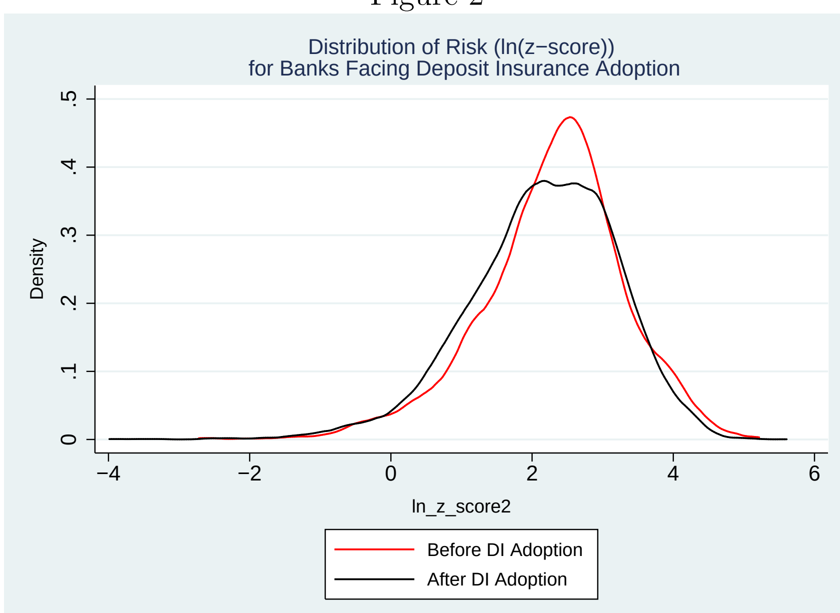


Figure 2



Note: These figures show the kernel density of the Capital-to-Assets ratio (top) and the log of z-score (bottom) *before* (in blue) and *after* (in white) deposit insurance adoption. The sample of banks is restricted to banks for which we have observations before and after deposit insurance adoption. A lower value signals an increase in the leverage (top)/ probability of default (bottom).

Figure 3

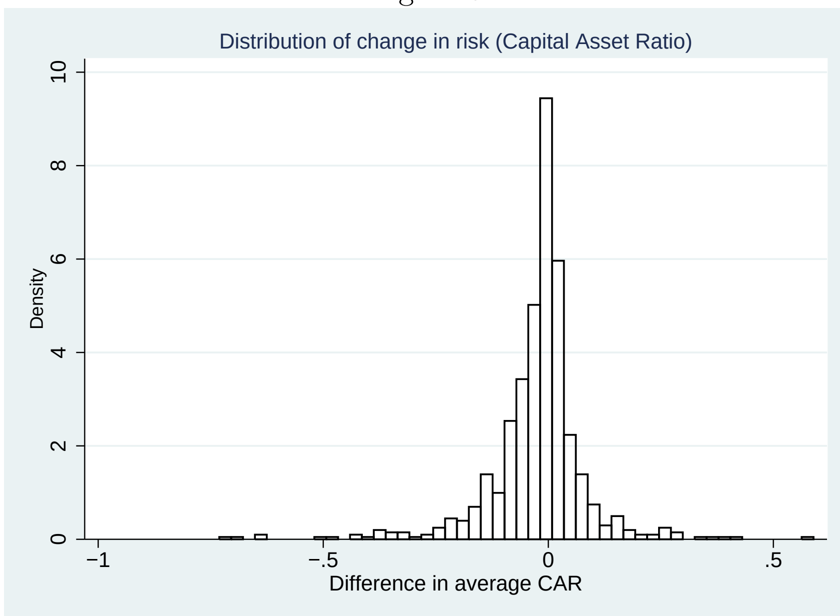
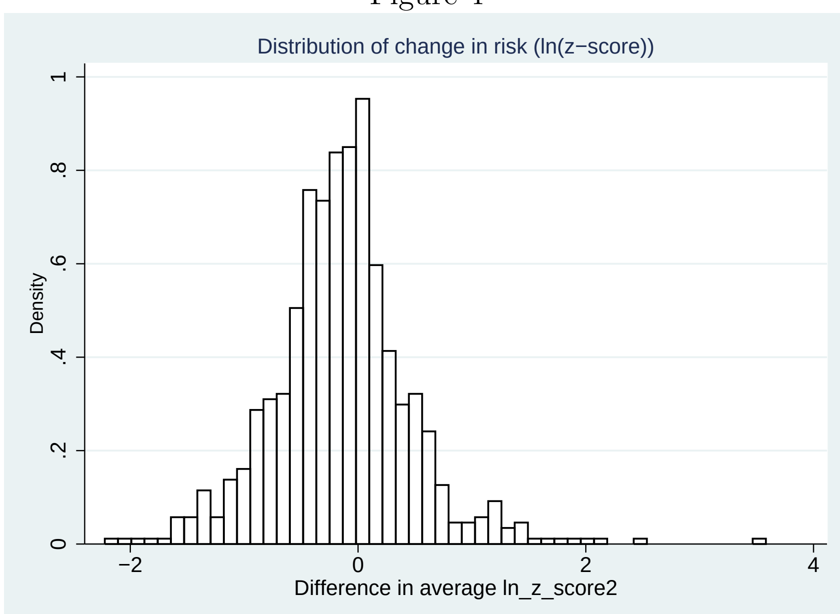


Figure 4



Note: These figures show the distribution of the difference between the average Capital-to-Assets ratio (top) and log of z-score (bottom) computed *after* and *before* deposit insurance adoption. The sample of banks is restricted to banks for which we have observations before and after deposit insurance adoption. A negative value indicates that the average Capital-to-Assets ratio (top)/log of z-score (bottom) is lower *after* adoption.

Table 21: Placebo Laws

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HHI index on deposit		0.0469**		0.0464**		0.0472**		0.0480**		0.0454**
		(0.0025)		(0.0030)		(0.0029)		(0.0021)		(0.0034)
GDP growth (annual %)		0.1011*		0.1025*		0.1003*		0.0984*		0.0858
		(0.0326)		(0.0299)		(0.0330)		(0.0376)		(0.0729)
Inflation (annual %)		0.0000		0.0000		0.0000		0.0000		0.0000
		(0.1332)		(0.1380)		(0.1317)		(0.1445)		(0.1538)
Log of GDP per capita		-0.0952*		-0.0963*		-0.0983**		-0.0962*		-0.0893*
		(0.0134)		(0.0112)		(0.0098)		(0.0123)		(0.0202)
Placebo for year -3	-0.0051	-0.0026								
	(0.2379)	(0.5428)								
Placebo for year -4			-0.0052	-0.0024						
			(0.2532)	(0.5901)						
Placebo for year -5					-0.0017	0.0017				
					(0.7267)	(0.7244)				
Placebo for year -6							0.0082	0.0082		
							(0.1179)	(0.1327)		
Placebo for year -7									0.0198**	0.0158**
									(0.0000)	(0.0008)
Observations	2,923	2,923	2,923	2,923	2,923	2,923	2,923	2,923	2,923	2,923
Number of id	755	755	755	755	755	755	755	755	755	755
Adjusted R-squared	0.0203	0.0415	0.0202	0.0415	0.0194	0.0414	0.0208	0.0428	0.0276	0.0464
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. In all the regression the dependent variable is the Capital-to-Assets ratio. *Placebo for year -"i"* is a dummy variable simulating for each country a deposit insurance adoption n years before the true adoption. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 22: Various log of z-score

CAR ROOA Stand. dev. ROAA	Contemporaneous Contemporaneous Sample Av.	Contemporaneous Mov. Av. (2 1 2) Sample Av.	Mov. Av. (2 1 2) Mov. Av. (2 1 2) Sample Av.	Contemporaneous Sample Av. Sample Av.	Contemporaneous Contemporaneous Instantaneous
Deposit Insurance	-0.1924***	-0.1780***	-0.1434***	-0.1724***	-0.1031***
	(0.0221)	(0.0223)	(0.0200)	(0.0200)	(0.0392)
HHI index on deposit	-0.0889*	-0.0681	-0.0489	-0.0990**	-0.5035***
	(0.0518)	(0.0514)	(0.0469)	(0.0494)	(0.0938)
GDP growth (annual %)	0.4881***	0.4443***	0.7217***	0.1918**	1.1979***
	(0.0873)	(0.0859)	(0.0746)	(0.0760)	(0.2178)
Inflation (annual %)	0.0001*	0.0001	0.0001	0.0000	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Log of GDP per capita	0.1110**	0.1018**	0.0849*	-0.0200	0.7022***
	(0.0488)	(0.0478)	(0.0452)	(0.0409)	(0.0843)
Observations	205,583	206,433	206,723	206,798	205,585
Number of id	18,814	18,814	18,814	18,812	18,816
Adjusted R-squared	0.0195	0.0182	0.0260	0.0159	0.0094
Bank FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

** $p<0.01$, * $p<0.05$. In all the column the dependent variable is the *logarithm of z-score*. The lines *CAR*, *ROAA* and *Stand. dev. ROAA* indicates how each of the z-score component is computed. *Mov Av. (2 1 2)* means Moving Average with a window centered around the contemporaneous value and including two lags and two leads. *Sample Av.* means average computed for each bank over the entire sample. *Instantaneous ROAA* reefers to the difference between contemporaneous value of ROAA and the bank sample average of ROAA. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 23: z-score regressions

	z-score					
Deposit Insurance	-5.1099**	-4.4356**	-1.4799*	-1.4841*	-1.3681*	-1.4484*
	(0.0011)	(0.0003)	(0.0422)	(0.0230)	(0.0150)	(0.0169)
HHI index on deposit		0.6840		2.6357		0.6204
		(0.7949)		(0.1001)		(0.6052)
GDP growth (annual %)		24.3423		-6.0878		-7.0794
		(0.2607)		(0.3754)		(0.3289)
Inflation (annual %)		0.0008		-0.0008		0.0000
		(0.4369)		(0.2167)		(0.9192)
Log of GDP per capita		-5.2500		3.3967		-2.8447
		(0.0840)		(0.4037)		(0.3409)
Observations	206,534	206,534	206,534	206,534	206,534	206,534
Number of id	18,815	18,815	18,815	18,815	18,815	18,815
Adjusted R-squared	0.0223	0.0237	0.0661	0.0662	0.0704	0.0706
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Ctry Specific Trend			Linear	Linear	Lin. & Quad	Lin. & Quad

** $p<0.01$, * $p<0.05$. In all the regression the dependent variable is the z-score. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 24: Sample of Listed Banks

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0186*	-0.0202*	-0.1748**	-0.2067**	-0.0251**	-0.0260**	-0.1607*	-0.1749**
	(0.0329)	(0.0131)	(0.0066)	(0.0011)	(0.0002)	(0.0002)	(0.0185)	(0.0039)
HHI index on deposit		-0.0159		-0.2432		0.0020		-0.0188
		(0.5667)		(0.3098)		(0.9228)		(0.9239)
GDP growth (annual %)		0.0687		0.8574*		-0.0262		-0.0252
		(0.0776)		(0.0110)		(0.4185)		(0.9217)
Inflation (annual %)		0.0000		0.0002		-0.0000		0.0000
		(0.5582)		(0.1188)		(0.5485)		(0.9259)
Log of GDP per capita		0.0095		0.2270		0.0316		0.9852**
		(0.7704)		(0.2947)		(0.4172)		(0.0003)
Observations	10,823	10,823	10,650	10,650	10,823	10,823	10,650	10,650
Adjusted R-squared	0.0138	0.0154	0.0195	0.0287	0.1243	0.1244	0.1230	0.1303
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country
Number of id	904	904	902	902	904	904	902	902
Ctry Specific Trend	None	None	None	None	Linear	Linear	Linear	Linear

** $p<0.01$, * $p<0.05$. This table presents results from regressions on the sample of banks publicly listed. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 25: Sample of Banks Active in 2007 and Sample Excluding Years Post-2007

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0232*	-0.1491**	-0.0182*	-0.1790**	-0.0246**	-0.2011**	-0.0171**	-0.1677**
	(0.0115)	(0.0046)	(0.0223)	(0.0004)	(0.0004)	(0.0000)	(0.0024)	(0.0000)
HHI index on deposit			0.0189	0.0032			0.0063	-0.0520
			(0.2827)	(0.9817)			(0.5777)	(0.5039)
GDP growth (annual %)			-0.0324	0.4411			0.0643*	0.6194*
			(0.6601)	(0.4253)			(0.0287)	(0.0447)
Inflation (annual %)			-0.0000**	0.0000			-0.0000	0.0001
			(0.0007)	(0.6758)			(0.9208)	(0.2833)
Log of GDP per capita			-0.0268	0.1720			-0.1023**	-0.4178**
			(0.0966)	(0.1654)			(0.0000)	(0.0030)
Observations	177,843	176,853	177,843	176,853	151,342	150,419	151,342	150,419
Number of id	15,164	15,164	15,164	15,164	18,825	18,809	18,825	18,809
Adjusted R-squared	0.0055	0.0206	0.0067	0.0219	0.0045	0.0149	0.0103	0.0176
Regression Type	FE	FE	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. The columns 1 to 4 present the results from regressions on the sample of banks that have an observation in 2007. It thus excludes all the banks that went bankrupt before 2007. The columns 5 to 8 present the results from regressions on the sample excluding years after 2007. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 26: Controlling for M&A

	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0215**	-0.1746**	-0.0180*	-0.1890**
	(0.0052)	(0.0001)	(0.0107)	(0.0000)
HHI index on deposit			0.0042	-0.1096
			(0.7369)	(0.2823)
GDP growth (annual %)			-0.0179	0.4902
			(0.7723)	(0.3084)
Inflation (annual %)			-0.0000	0.0001
			(0.7427)	(0.3030)
Log of GDP per capita			-0.0320*	0.1234
			(0.0349)	(0.2948)
Observations	204,337	202,898	204,337	202,898
Number of id	18,545	18,534	18,545	18,534
Adjusted R-squared	0.0055	0.0186	0.0067	0.0200
Regression Type	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES
Cluster	Country	Country	Country	Country

** $p<0.01$, * $p<0.05$. This table presents the results from regressions on the sample excluding bank observations having a growth of assets higher than 50% from one year to another. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.

Table 27: Specification with bank-specific covariates

	CAR	ln(z-score)	CAR	ln(z-score)	CAR	ln(z-score)
Deposit Insurance	-0.0205**	-0.1887**	-0.0200**	-0.1412**	-0.0166*	-0.1181**
	(0.0029)	(0.0000)	(0.0021)	(0.0002)	(0.0206)	(0.0007)
Cost To Income Ratio	0.0382**	0.0433	0.0387**	0.0469	0.0388**	0.0484
	(0.0000)	(0.4504)	(0.0000)	(0.3892)	(0.0000)	(0.3685)
Net Interest Margin	0.1981*	1.5741*	0.1886*	1.4678*	0.1964*	1.5279*
	(0.0301)	(0.0263)	(0.0327)	(0.0305)	(0.0220)	(0.0197)
Total deposits/liabilities	-0.0302*	0.0083	-0.0361*	-0.0369	-0.0349*	-0.0259
	(0.0500)	(0.8868)	(0.0150)	(0.5232)	(0.0172)	(0.6447)
Liquid asset/asset	0.0475	0.1233	0.0463	0.1030	0.0464	0.1000
	(0.0759)	(0.2408)	(0.1053)	(0.3762)	(0.1097)	(0.4000)
HHI index on deposit	0.0035	-0.0625	0.0159	0.0847	0.0150	0.0852
	(0.8211)	(0.5602)	(0.2213)	(0.2757)	(0.2700)	(0.2475)
GDP growth (annual %)	0.0032	0.5059	-0.0634	-0.2599	-0.0464	-0.2073
	(0.9493)	(0.2804)	(0.1154)	(0.3397)	(0.2497)	(0.4305)
Inflation (annual %)	0.0000	0.0002	0.0000	0.0001	0.0000	0.0002
	(0.7413)	(0.4064)	(0.7825)	(0.4701)	(0.3264)	(0.1481)
Log of GDP per capita	-0.0260	0.1340	-0.0261	0.3168	-0.0677	-0.0126
	(0.1583)	(0.3031)	(0.4848)	(0.1359)	(0.1283)	(0.9526)
Observations	204,53	203,729	204,530	203,729	204,530	203,729
Number of id	18,726	18,722	18,726	18,722	18,726	18,722
Adjusted R-squared	0.0966	0.0334	0.1130	0.0663	0.1186	0.0756
Regression Type	FE	FE	FE	FE	FE	FE
FE	Bank	Bank	Bank	Bank	Bank	Bank
Year FE	YES	YES	YES	YES	YES	YES
Cluster	Country	Country	Country	Country	Country	Country
Ctry Specific Trend	None	None	Linear	Linear	Lin.& Quad.	Lin.& Quad.

** p<0.01, * p<0.05. These regressions include bank-specific covariates taken from BankScope. Standard errors clustered at the country level. *p-value* in parentheses. Two-way Fixed-effects model. All regressions includes a constant term. The Adjusted R-squared does not take into account the contribution of bank fixed effects to the explained variance.